Internet Appendix:

# Real Disinvestments and the Distress Anomaly: Evidence from Stocks, Bonds, and Loans

Shuwen Yang, Kevin Aretz, and Yafei Zhang

In this Internet Appendix, we offer empirical evidence and mathematical derivations omitted from our main paper. In Section IA.1, we start off with looking into the coverage and quality of our bond and loan price data in the stock-bond and stock-bond-loan-asset samples (Tables IA.1 to IA.3 and Figures IA.1 and IA.2). Section IA.2 explores the characteristics and beta loadings of the stock and bond portfolios in the stock-bond sample and their long-horizon pricing (Tables IA.4 and IA.5 and Figure IA.3). Section IA.3 investigates single-bond portfolios double-sorted on distress and bond ratings (Table IA.6). In Section IA.4, we consider the characteristics and beta loadings of the stock, bond, loan, and firm-asset portfolios in the stock-bond-loan-asset sample and their long-horizon pricing (Tables IA.7 and IA.8 and Figure IA.4). Section IA.5 offers the results from several robustness tests on the pricing of distress risk in stocks, bonds, loans, and firm-assets, shedding light on the effects of matrix prices (Tables IA.9 to IA.12), illiquidity and liquidity risk (same tables), changes in bond or loan ownership spurred by mergers and acquisitions (M&As; Tables IA.13 to IA.16), and omitted and/or underrepresented asset classes in our asset return calculations (Tables IA.17 to IA.20 and Figure IA.5). In Section IA.6, we use Fan and Sundaresan's (2000) model to formally demonstrate that Garlappi et al.'s (2008) and Garlappi and Yan's (2011) shareholder advantage theory cannot explain a negative debt distress premium. Finally, Section IA.7 derives the quasi-closed-form solutions for our real options model in Section IV of our main paper, offers details about the Monte Carlo simulations used to derive stock and debt values from that model, and gives comparative statics for the disinvestment ability-expected stock or debt return results extracted from the model.

## IA.1 Sample Data Coverage and Quality

In this section, we replicate all the exercises in the appendixes and online appendixes of Choi (2013) and Choi and Richardson (2016) to corroborate that our bond and loan samples are reasonably comprehensive and that the prices in them are of a high quality. Doing so is important since our bond sample mixes matrix prices from Lehman Brothers, Datastream, and ICE, quotes from Lehman Brothers and Datastream, and transaction prices from NAIC and TRACE (see Section 1 in our main paper). Conversely, our loan sample mixes quotes from LoanConnector and transaction prices from CLO-i (see Section 2 in that same paper). Given that, it is unclear to what extent the bond and loan samples span the CRSP-Compustat universe, the bond sample the Mergent FISD universe, and the loan sample the Dealscan universe. Moreover, as especially matrix prices but also quotes can be of a low quality, it is unclear to what extent our samples suffer from price staleness.

We first look into the coverage of our stock-bond and stock-bond-loan-asset samples. We then evaluate the quality of the stock, bond, and loan data, especially with respect to staleness.

### IA.1.1. Bond and Loan Data Coverage

We now investigate the coverage of our stock-bond and stock-bond-loan-asset samples. To that end, we first replicate the sample-coverage statistics in Table A.1 of Choi and Richardson (2016) benchmarking their stock-bond sample firms against the CRSP-Compustat universe for our two samples.[1] More specifically, Internet Appendix Table IA.1 gives the number of observations, mean and median market assets, and median book and market leverage for several samples in Panel A and for several credit-rating-based subsamples in Panel B. In addition, Panel A also reports the median proportion of a firm's debt book value (the sum of short and long-term debt) covered by the outstanding bond balance

[1] We omit their statistics for the sample of bonds with a non-missing implied volatility from Optionmetrics (the final column in Panel A of their table) since we do not require that variable for our purposes.

in the stock-bond sample and the outstanding bond plus loan balance in the stock-bond-loan-asset sample. While the samples in Panel A are the entire CRSP-Compustat universe, the sub-universes of levered and non-levered firms, the entire stock-bond firm sample and the subsample with assets above $100 million, and the entire stock-bond-loan-asset firm sample and the subsample with assets above $100 million, the subsamples in Panel B are based on the stock-bond and the stock-bond-loan-asset samples. In line with Choi and Richardson (2016), we calculate market assets as the market equity value plus the book debt value and use entity ratings to form the subsamples in Panel B.

Despite the differences in data sources and sample periods, Internet Appendix Table IA.1 yields bond-sample results in close agreement with those obtained in Table A.1 in Choi and Richardson (2016).[2] In particular, we also find that our bond sample is a relatively small (about 15%) subsample of the entire CRSP-Compustat universe featuring larger (mean market assets: $21-vs.-$4 billion) and more levered (median market leverage: 1.52-vs.-1.24) firms (see Panel A). In accordance, the corresponding numbers in Choi and Richardson (2016) are about 19%, $8.3-vs.-$2.0 billion,[3] and 1.45-vs.-1.18, respectively. The median proportion of book debt captured by the outstanding bond balances of our stock-bond sample firms is about 76%, also not too distant from the about 69% calculated by them. Switching to the ratings-based subsamples of our stock-bond sample in Panel B, it is obvious that while market asset values tend to be higher for better-rated firms, leverage and the proportion of book debt covered by outstanding bond balances tend to be lower for them, also in agreement with the statistics in Panel B of Table A.1 in Choi and Richardson (2016).

Notwithstanding the similarities, a striking difference between Internet Appendix Table IA.1 and Choi and Richardson's (2016) Table A.1 lies in the number of observations in our and their stock-bond samples. To be specific, while our stock-bond sample period is not only more recent (which is relevant since data coverage usually rises over time) but also three years longer than theirs, the number of observations is about the same (284k-vs.-286k in our-vs.-their sample, respectively). The reason,

[2] In comparison to us, Choi and Richardson (2016) study bond prices from Lehman Brothers and the Thomson Reuters Bond Pricing Database (rather than Lehman Brothers, Datastream, ICE, NAIC, and TRACE) over the sample period from January 1980 to December 2012 (rather than January 1986 to December 2020).

[3] Note that since we report nominal (and not real) dollar values, it is unsurprising that our dollar values are higher than theirs due to our more recent sample period. Notwithstanding, we both find that the average firm in the CRSP-Compustat universe is about 4-5 times smaller than the corresponding firm in the stock-bond sample.

however, is that, in contrast to Choi (2013) and Choi and Richardson (2016), we follow many recent studies in the bond pricing literature (including, e.g., Bai et al. (2019), Dick-Nielsen et al. (2025), Dickerson et al. (2025), and Bartram et al. (2025)) in excluding "non-standard bonds" from our bond return calculations, only using their market capitalizations in our asset-return weights (see Sections 1 and 2 in our main paper). Also counting these non-standard bonds, the number of firm observations in our stock-bond sample shoots up to a more reasonable 556,174.

The stock-bond-loan-asset sample results in Internet Appendix Table IA.1 often align with the stock-bond results. In particular, while the stock-bond-loan-asset sample is an even smaller (3%) subsample of the CRSP-Compustat universe, it is also skewed toward larger (mean market assets: $12-vs.-$4 billion) and more levered (1.72-vs.-1.24) firms (see Panel A).[4] More noteworthily, the median proportion of book debt captured by the outstanding bond plus loan balances of our stock-bond-loan-asset sample firms is 93%, close-to-identical to the 94% calculated by Choi and Richardson (2016). Looking into the ratings-based subsamples in Panel B, market asset values again tend to be higher for better-rated firms, but neither leverage nor the proportion of book debt covered by the outstanding bond and loan balances form a discernable pattern over the subsamples. Finally, the proportion of book debt covered by those balances consistently lies above 90% — except for the often thinly-populated AAA, AA, and A (39-82%) and the C (66%) rated subsamples.

We next compute the proportions of the aggregate outstanding bond balance in the Mergent FISD universe captured by the corresponding balance in our stock-bond sample and of the aggregate outstanding loan balance in the Dealscan universe captured by the corresponding balance in our stock-bond-loan-asset sample. We compute those proportions first by sample month and then average over time. In further agreement with both Choi (2013) and Choi and Richardson (2016), the bond proportion is 84%, not too far off from the 90% calculated in the two other studies. Averaging the sample-month-specific bond proportions by calendar year, Internet Appendix Figure IA.1 shows that they initially decline from about 81% in 1986 to only about 65% in 1994, but then tend to increase

[4]We are unable to contrast our stock-bond-loan-asset sample statistics with the corresponding statistics for Choi and Richardson's (2016) bond-loan sample since Choi and Richardson (2016) do not separately report these. The reason is that they impute loan returns for firms with bonds but no traded loans from bond returns, so that their bond sample firms are identical to their bond-loan sample firms including those with imputed values.

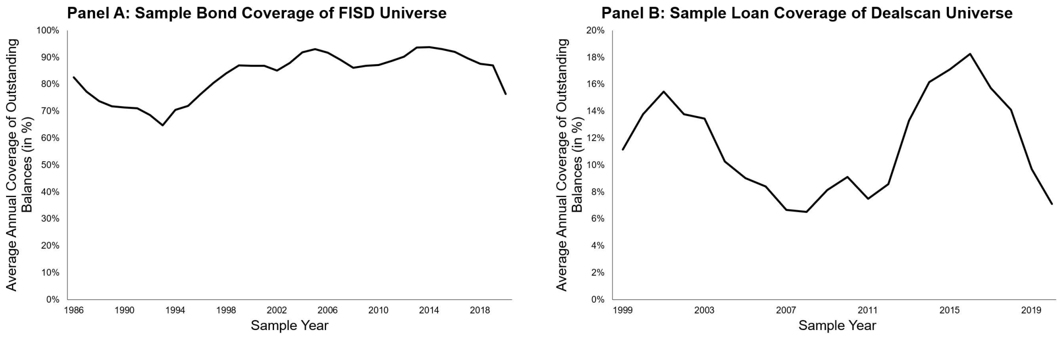


**Figure IA.1: The Coverage of our Bond and Loan Sample Data**

The figure plots the proportions of the aggregate Mergent FISD outstanding bond balance captured by our sample bond data (Panel A) and of the aggregate Dealscan loan outstanding balance captured by our sample loan data (Panel B) over the 1986 to 2020 and the 1999 to 2020 sample periods, respectively. We calculate the proportions first by sample month and then average over year. We use only public firms and those bonds and loans not excluded by our sample filters (see Section 1 in our main paper) to calculate the aggregate balances.

over the remaining period (see Panel A). Conversely, the loan proportion is about 12%. Also averaging the sample-month-specific loan proportions by calendar year, Internet Appendix Figure IA.1 reveals that they lie between 6% and 18% over the sample period from 1999 to 2020 (see Panel B).

### IA.1.2. Data Quality

We next study the quality of our stock, bond, and loan data. As stressed in Choi (2013) and Choi and Richardson (2016), there may be concern that our bond and loan samples suffer from price staleness because the bond (loan) sample mixes matrix prices, quotes, and transaction prices (quotes and transaction prices). Yet, since matrix prices and quotes are only indicative, implying that investors cannot be sure that they can trade at them, it may be less urgent for dealers to update them in response to news. While we take the same steps as the above studies to minimize price staleness (i.e., we study monthly rather than higher-frequency returns and consider value as well as equally-weighted portfolios in all our tests), we now also look into the frequency of zero-price-change observations, autocorrelations and cross-correlations, and direct comparisons of matrix prices and quotes with transaction prices, to assess the magnitude of any remaining staleness. As demonstrated by Scholes and Williams (1977), staleness induces firm (portfolio) level returns to be negatively (positively) autocorrelated. Also, it allows the returns of asset classes suffering less from staleness (as, e.g., stocks) to predict those of asset classes suffering more from it (as, e.g., bonds and loans).

We first look into the data quality of our stock-bond sample. Having done so, we then switch to investigating the data quality of our stock-bond-loan-asset sample.

*IA.1.2.1. The Stock-Bond Sample*

We start off with assessing the staleness in our stock-bond sample. To do so, we replicate Table C.1 in Choi and Richardson (2016) giving the proportion of zero bond-price-change observations (Panel A), the first three firm and (value-weighted) portfolio-level autocorrelations of our stock and bond returns (Panel B), and the cross-correlations of the bond return with the contemporaneous stock return and its first three lags and vice versa (Panel C) in our Internet Appendix Table IA.2. We calculate each of the statistics for both the entire sample and credit-rating-based subsamples. Panel A of our table shows that the whole-sample proportion of zero-bond-price change observations at the single-bond or firm-portfolio[5] level is 1.7% and 6.2%, slightly lower than the corresponding numbers in Choi and Richardson (2016), 2.0% and 9.9%, all respectively. The slightly smaller proportions generated by our sample are perhaps unsurprising since, in contrast to their sample, ours is heavily (about 50%) skewed toward transaction prices which are less stale than quotes. Still, the proportion of zero-bond-price observations at the single-bond and firm-portfolio level markedly rise over the credit-rating subsamples in both of our samples, with the single-bond-level proportion, for example, increasing from 0.03% (1.9%) for the best to 4.8% (7.8%) for the worst-rated subsample in case of our (their) sample.

Looking into the autocorrelations in Panel B, our stock first-order autocorrelations at the firm (subpanel B.1) and portfolio (subpanel B.2) level are similar to Choi and Richardson's (2016). While the stock autocorrelation at the portfolio level, for instance, rises from –0.05 to 0.06 over their credit-rating subsamples (average absolute value: 0.06), the corresponding rise over our subsamples is from –0.05 to 0.08 (average absolute value: 0.08). More importantly, our firm and portfolio-level autocorrelations for bonds are also similar to theirs. While the average absolute first-order bond autocorrelation at the firm

[5]The firm-portfolio statistic gives the proportion of firm-month observations for which at least one of all the bonds of some firm does not exhibit a price change over some month.

and portfolio level is, for example, 0.07 and 0.12 over their credit-rating subsamples, it is 0.06 and 0.10 over ours, all respectively. Interestingly, however, our bond autocorrelations are far more stable (i.e., increase far less) over those subsamples than theirs, especially at the portfolio level. The reason may once again be that, in contrast to their bond sample, ours contains a large proportion of transaction prices from NAIC and TRACE, and those prices are likely to be less susceptible to staleness.

Panel C confirms that the cross-correlations between stock and bond returns also align across Choi and Richardson's (2016) and our sample. While the average contemporaneous cross-correlation is, for example, 0.31 over their subsamples, it is 0.26 over ours. More importantly, while the absolute cross-correlation between bond returns and one-month-lagged stock returns is, for instance, on average 0.07 and never exceeds 0.15 over their subsamples, it is on average 0.06 and never exceeds 0.14 over ours. Given that even a cross-correlation of 0.15 implies that only 2.25% of the variations in bond returns can be forecasted with lagged stock returns, we can conclude that bond returns are close-to-unpredictable with stock returns in our and Choi and Richardson's (2016) sample.

We finally also contrast the bond matrix prices and quotes from ICE and Datastream with the corresponding transaction prices from NAIC and TRACE. To that end, we compute the absolute difference between those two type of prices scaled by the transacton price separately for the ICE and Datastream matrix prices and quotes.[6] We then take the mean or median difference by calendar year and average that over time. The overall mean and median absolute difference for the ICE prices are 0.87% and 0.44%, respectively, within the usual bid-ask spread of about one percent for liquid bonds (see Choi and Richardson (2016)). Strikingly, however, Internet Appendix Figure IA.2 shows that the difference depends on the economic state, with it, for example, markedly rising to an average of about two percent at the onset of the global financial crisis (see Panel A). In contrast, the overall mean and median absolute difference for the Datastream prices are 2.10% and 0.95%, respectively, significantly higher than those for the ICE prices. Notwithstanding, the figure reveals that the Datastream differences also rise during crises. The worse quality of the Datastream bond data is unlikely to be an issue for us since only about 10% of our stock-bond sample observations

[6] We are unable to perform a similar analysis on Lehman Brothers bond prices since the Lehman Brothers sample period does not overlap with the NAIC and TRACE sample periods.

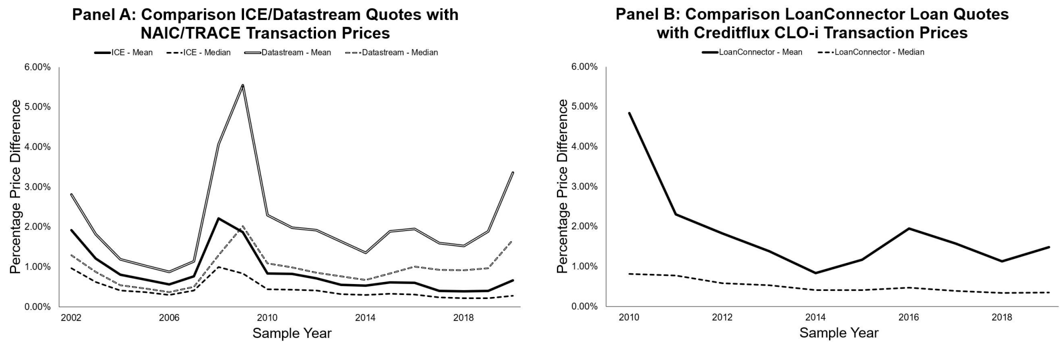


**Figure IA.2: The Quality of our Bond and Loan Price Data**

The figure plots the mean and median absolute percentage differences between either our sample bond (Panel A) or loan (Panel B) quotes and the corresponding transaction prices over the sample periods from 2002 to 2020 and 2010 to 2020, respectively. While Panel A contrasts bond quotes from either ICE or Datastream with the corresponding transaction prices from both NAIC and TRACE, Panel B contrasts loan quotes from LoanConnector with the corresponding transaction prices from Creditflux CLO-i. We calculate the absolute percentage difference as the absolute price difference scaled by the transaction price. We then take the mean (solid line) or the median (broken line) by calendar year.

come from Datastream. Also, we later show in this Internet Appendix that replicating our main empirical tests using only bond transaction prices does not materially change our conclusions.

#### *IA.1.2.2. The Stock-Bond-Loan-Asset Sample*

We next consider the staleness in our stock-bond-loan-asset sample. To do so, we once again replicate Table C.1 in Choi and Richardson (2016) giving the proportion of zero-loan-price change observations (Panel A), the first three firm and (value-weighted) portfolio-level autocorrelations of our stock, bond, and loan returns (Panel B), and the cross-correlations between the bond or loan return and the contemporaneous stock return and its first three lags and vice versa (Panel C) in our Internet Appendix Table IA.3. Panels B and C of our table corroborate that the stock and bond autocorrelations and their cross-correlations are highly similar across the stock-bond and stock-bond-loan-asset samples. While the whole-sample stock and bond firm-level autocorrelations are, for example, –0.01 and –0.02 in the stock-bond sample (average absolute values over the credit-rating subsamples: 0.02 and 0.06), the corresponding numbers for the stock-bond-loan-asset sample are –0.01 and –0.04 (average absolute values: 0.06 and 0.07), all respectively (contrast with Internet Appendix Table IA.2). Moreover, while the cross-correlation between bond and one-month-lagged stock returns is 0.06 in the stock-bond sample, the corresponding number for the stock-bond-loan-asset sample is 0.08. Given those similarities in the stock and bond statistics, we focus on the loan statistics in the remainder of this section.

Panel A of Internet Appendix IA.3 suggests that the loan prices in the stock-bond-loan-asset sample are far less likely to change than the bond prices in the stock-bond sample (contrast with Internet Appendix Table IA.2). More specifically, while there are only 1.7% zero-bond-price-change observations in the stock-bond sample, the corresponding number for loans in the stock-bond-loan-asset sample is a whopping 33.9%. Interestingly, the panel further demonstrates that the 33.9% is almost exclusively driven by an even higher proportion in the quotes (34.2%) rather than transaction price (1.0%) data. Notwithstanding, Choi and Richardson (2016) caution that a zero quote change does not necessarily indicate price staleness, but could — especially for financial claims at the top of the capital structure — simply imply stable interest rate and default risk expectations. Assuming that changes in expectations trigger trading, we find some support for that conjecture, showing that the proportion of zero-quote-change observations conditional on at least one trade over the month drops down to 0.2%. Surprisingly, and different from bonds, the proportion of zero-loan-price-change observations does not vividly increase over the credit-rating-based subsamples.

Looking into the autocorrelations in Panel B, the first-order loan autocorrelations at the firm-level are reasonably close-to-zero for the whole sample (0.06) and the subsamples (average absolute value: 0.07; see subpanel B.1). In contrast, the corresponding autocorrelations at the portfolio-level in subpanel B.2 are much more positive, with the whole-sample value being 0.43 and the subsample values rising from 0.02 for the best-rated to 0.32 for the worst-rated firms (average absolute value: 0.28). Conversely, the second-order autocorrelations at the portfolio level are much closer to zero again, with the whole-sample value being 0.14. The implication is thus that while the firm-level autocorrelations do not point to great staleness in our sample loan prices, the portfolio-level autocorrelations suggest that when the loan prices are updated in response to changes in interest rate and/or default risk expectations, those updates occur asynchronously over a period of about 1-2 months, especially for the loans of firms with weak credit ratings.

Studying the cross-correlations between stocks and loans in subpanel C.2 in Panel C reveals that the whole-sample contemporaneous cross-correlation is 0.22, not too far from the corresponding cross-correlations between stocks and bonds in the stock-bond (0.26) and stock-bond-loan-asset (0.30) sample (contrast with the stock-bond values in Panel C of Internet Appendix Table IA.2 and the current table, respectively). Notwithstanding, the whole-sample cross-correlation of the loan return with the one-month-lagged stock return, 0.15, is higher than the corresponding cross-correlations of bond returns in either sample, 0.06-0.08. Also, while the cross-correlation of bond returns with lagged stock returns never exceeds 0.14 over the credit-rating subsamples in either sample, the corresponding loan cross-correlation can reach up to 0.22 for the C-rated-firm subsample. Despite that, even the cross-correlation of 0.22 implies that only 4.84% of the variations in loan returns can be predicted with one-month-lagged stock returns. We deem that number economically small.

We finally also contrast the loan quotes from LoanConnector with the corresponding transaction prices from CLO-i. While we conduct the comparisons analogously to the corresponding bond-price comparisons in Section IA.1.2.1. of this Internet Appendix, we restrict our attention to the period from 2010 to 2020 since the CLO-i transaction-price cross-sections become reasonably wide only from the earlier year onward. The overall mean and median absolute differences are 1.85% and 0.51%, somewhat larger than the corresponding differences for the ICE bond prices, 0.87% and 0.44%, but lower than those for the Datastream bond prices, 2.10% and 0.95%, all respectively (contrast with the numbers in Section IA.1.2.1.). Plotting the calendar-year mean and median differences over time, Figure IA.2 in this Internet Appendix shows that they also depend on the economic state, with them again being particularly high at the end of the global financial crisis.

Overall, this section suggests that our stock-bond sample is an almost comprehensive sample of the Mergent FISD universe, while the stock-bond-loan-asset sample is a markedly smaller subsample of the Dealscan universe, with both, however, featuring larger firms with a higher financial leverage than the average CRSP-Compustat firm. Looking into the proportion of zero-price-change observations, autocorrelations and cross-correlations, and absolute price differences between matrix prices/quotes and transaction prices, it further reveals that our bond sample is of a reasonably high quality comparable to that of the Choi (2013) and Choi and Richardson (2016) samples, whereas the loan sample is of a slightly weaker albeit (in our opinion) still acceptable quality.

## IA.2 Characteristics, Beta Loadings, and Long-Horizon Distress Pricing of the Stock-Bond Portfolios

In this section, we investigate the characteristics, beta loadings, and the long-horizon distress premiums of the stock and bond distress portfolios in the stock-bond sample analyzed in Section B of our main paper. Starting with the characteristics, Internet Appendix Table IA.4 reports the mean characteristics of the stock (Panel A) and bond (Panel B) portfolios, first calculated by portfolio and sample month and then averaged over time. The stock characteristics include the market beta, market capitalization ("size"), the book-to-market ratio, momentum, asset growth, and profitability. The bond characteristics include the bond market beta, value-weighted average and aggregate bond market capitalization, the years-to-maturity, the credit rating, the coupon rate, downside risk, bond reversal, liquidity beta, and illiquity. See Table A1 in Appendix A at the end of the main paper for details about the characteristics from the main paper. The coupon rate is the coupon-to-price ratio, the liquidity beta the loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see Lin et al. (2011)), and illiquidity the daily-price-change autocovariance (see Bao et al. (2011)).[7]

Panel A of Internet Appendix Table IA.4 suggests that the mean characteristics of the stock portfolios align with those found in the literature (see, e.g., Campbell et al. (2008)). Specifically, highly distressed stocks tend to be small, unprofitable value stocks with a high market beta. Interestingly, however, both extremely high and low distress stocks tend to be high-investment loser stocks, creating an inverted U-shaped (U-shaped) relation between the intermediate-term past return (asset growth) and distress risk. Conversely, Panel B reveals that highly distressed bonds tend to be small (at least in terms of their value-weighted market capitalization), short-maturity-time, and high-coupon-rate bonds with low credit ratings. Moreover, they tend to have a high value-at-risk (as measured through

[7]Since we require daily data to calculate the bond illiquidity and the bond liquidity risk variables, we highlight that we can calculate their mean values only over the sample period from July 2002 to December 2020.

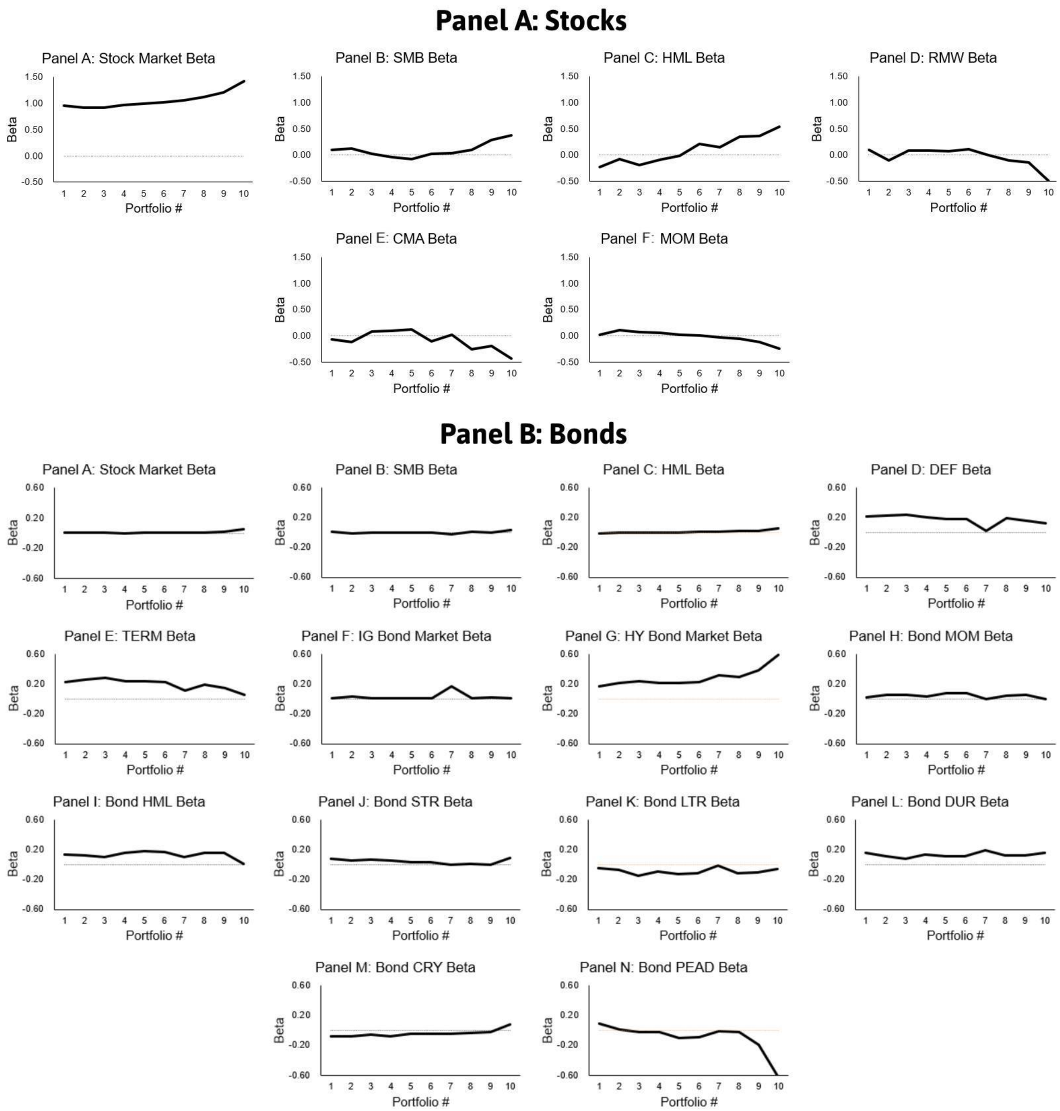


**Figure IA.3: Factor Betas of the Stock-Bond Portfolios**

The figure shows the full-sample betas of the stock (Panel A) and firm-specific bond (Panel B) portfolios univariately sorted on distress risk on the FF6S and SB14 factor model factors, respectively. See Appendix A at the end of the main paper for more details about the construction of the factors included in the two factor models.

*DownsideRisk*), a low one-month-lagged past return (as captured by *Reversal*), a high liquidity beta, and a high illiquidity. Finally, both the bond market beta as well as the aggregate bond capitalization form, somewhat surprisingly, an inverted U-shape over the distress portfolios.

In Figure IA.3, we look into the full-sample beta loadings of the same stock (Panel A) and bond

(Panel B) distress portfolios on the six factors of the FF6S model and the 14 factors of the SB14 model, respectively. In agreement with the insight that a stock's co-movement with some set of stocks often signals the stock's identity (see Fama and French (2016)), the stock portfolio betas largely align with their mean characteristics. In particular, Panel A of the figure suggests that highly distressed stocks have high MKT, SMB, and HML but low RMW betas, in line with them being small, unprofitable value stocks with amplified market betas. Slightly different from the mean characteristics, the CMA betas, however, also decline over the distress portfolios, whereas the MOM betas are close-to-flat over them. Switching to the bond portfolios, Panel B reveals that, in contrast to the stock portfolio betas, the bond portfolio betas often do not strongly align with their mean characteristics, with most of them being virtually flat over the portfolios. The exceptions are the term-spread (TERM), the high-yield bond market portfolio (HY Bond Market), and the post earnings-announcement drift (Bond PEAD) betas. Consistent with highly distressed bonds having a short maturity time (low ratings and a high downside risk), the TERM (high-yield bond market) beta drops (rises) over the portfolios. Conversely, the bond PEAD beta markedly drops over the portfolios.

Finally, Internet Appendix Table IA.5 tabulates the mean returns of the high-minus-low stock (Panel A) or bond (Panel B) distress spread portfolios in the stock-bond sample separately for each of the twelve months after portfolio formation, where we use both the standard (Ret=S) and the BGN (Ret=BGN) methodology to calculate bond returns. In the value and equally weighted sorts, we calculate the mean returns as the intercepts ("alphas") obtained from regressing the value or equally weighted stock (bond) spread portfolio return on the contemporaneous returns of the FF6S (SB14) factor-model factors. In the FM regressions, we first regress the stock (bond) return on nine distress portfolio dummy variables indicating to which of the final nine portfolios the stock (bond) belongs (i.e., we omit the dummy for the first portfolio) and the controls also used in column (1) ((4)) of Table 3 of our main paper and measured until the start of the return month. We then set the mean return to the coefficient on the last distress portfolio dummy variable, capturing the mean spread return between distress deciles 10 and 1 after accounting for the controls. We stress that the value-weighted standard-return stock and bond results in Panels A and B of the table are identical to the stock and bond results plotted in Figure 2 of our main paper, respectively.

The table corroborates our claim in the main paper that the stock and bond distress premiums in the stock-bond sample dissipate only slowly over time. In particular, while both premiums are close-to-consistently significant over the first six months after portfolio formation, they are also significant over single months over the last six. For example, the value-weighted standard-return bond premium is strongly significant over months $t$ to $t+3$, only weakly significant over month $t+4$, strongly significant again over months $t+5$ and $t+6$, but then insignificant over month $t+7$. Given that distressed stocks and bonds tend to be smaller than their counterparts, the equally-weighted portfolios overweight distressed stocks and bonds relative to the value-weighted portfolios, often inducing the distress premiums obtained from them to remain significant for longer. In contrast to the portfolio sorts, the FM regressions suggest that the bond distress premium remains significant for only 2-3 months, presumably because they control for bond factors differently from the portfolio sorts. As always, the standard and BGN bond returns yield highly similar conclusions.

## IA.3 Portfolios Double-Sorted on Distress and Credit Ratings

Avramov et al. (2022) show that single corporate bonds with worse credit ratings earn lower mean returns than those with better ones, also pointing to a negative bond distress premium. Since Hilscher and Wilson (2017), however, reveal that ratings are a weak proxy for physical and more strongly reflect risk-neutral distress risk, it is unlikely that our evidence is driven by Avramov et al.'s (2022). To verify that claim, we next run a dependent double portfolio sort, either sorting our *single* sample bonds first into rating classes and then distress portfolios or vice versa. To be specific, we classify bonds with a most recent rating at the end of month $t-1$ of at least double-A as high investment grade, those with a rating below double-A but at least triple-B as low investment grade, and all others as speculative. Conversely, we sort them into distress portfolios according to the tercile breakpoints of the distress distribution on the same date. We value-weight the portfolios and hold them over month $t$. Within each rating (distress) portfolio, we form a spread portfolio long the top distress tercile (the speculative grade) portfolio and short the bottom tercile (the high investment grade) portfolio.

Internet Appendix Table IA.6 gives the double portfolio sort results. While Panel A focuses on the sort first into rating and then distress portfolios, Panel B examines the reverse sort. Conversely, while columns (1), (3), and (5) report the mean single-bond numbers, the plain numbers in columns (2), (4), and (6) are monthly SB14 alphas (in %) and those in square brackets Newey-West (1987) *t*-statistics. The table suggests that controlling for ratings, the SB14 alphas still drop significantly over the distress portfolios. Looking into low-investment-grade bonds in columns (3) and (4) of Panel A, we, for example, find that the SB14 alpha still decreases by 0.11% (*t*-statistic: –3.62). Conversely, controlling for distress risk, the SB14 alphas are either *higher* for worse-rated bonds or do not relate to ratings. Considering the middle default tercile in columns (3) and (4) of Panel B, we, for example, find that the SB14 alpha changes by a mere 0.03% (*t*-statistic: 0.34). The key lesson to take away is that while our results subsume those of Avramov et al. (2022), theirs do not subsume ours.

## IA.4 Characteristics, Beta Loadings, and Long-Horizon Distress Premiums of the Stock-Bond-Loan-Asset Portfolios

In this section, we study the characteristics, beta loadings, and the long-horizon distress premiums of the stock, bond, loan, and firm-asset distress portfolios in the stock-bond-loan-asset sample analyzed in Section C of our main paper. Starting with the characteristics, Internet Appendix Table IA.7 reports the mean characteristics of the stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) portfolios, first calculated by portfolio and sample month and then averaged over time. While the stock and bond characteristics in Panels A and B are the same as those in the same panels in Internet Appendix Table IA.4, respectively, the loan characteristics in Panel C include the value-weighted average and aggregate loan capitalization ("size") and the years-to-maturity and the firm-asset characteristics in Panel D the aggregate firm-asset capitalization. See Section IA.2 in this Internet Appendix and the references in there for details about the characteristics.

Panels A and B of Internet Appendix Table IA.7 suggest that the stock-bond-loan-asset sample

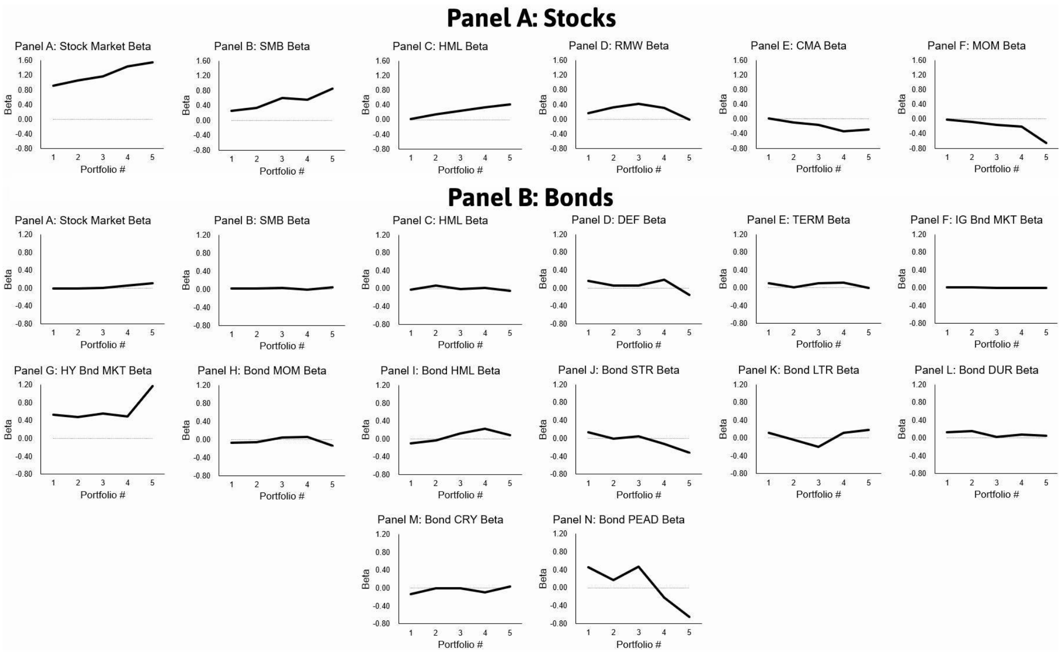


**Figure IA.4: Factor Betas of the Stock-Bond-Loan-Asset Portfolios**

generally produces stock and bond distress-characteristic relations in agreement with those produced by the stock-bond sample. In particular, highly distressed stocks again tend to be small, unprofitable value stocks with a high market beta. Interestingly, however, they now also tend to be loser stocks with an asset growth similar to other stocks. Conversely, highly distressed bonds again tend to be (slightly) smaller, short-maturity-time, and high-coupon-rate bonds with low credit ratings. Also as before, they tend to have a high value-at-risk, a low one-month-lagged past return, a high liquidity beta, and a high illiquidity. Noteworthily, however, they now also have markedly higher bond market betas but an aggregate bond market capitalization indistinguishable from other bonds.

The loan characteristics in Panel C show that while the value-weighted average loan capitalization forms a pronounced inverted U-shape over the distress portfolios, the aggregate loan capitalization is far more flat over them. Analogous to the bond portfolio characteristics in Panel B, highly distressed loans also tend to have a short maturity time. Finally, the firm-asset characteristics in Panel D suggest that the aggregate firm-asset capitalization strongly drops over the portfolios.

In Figure IA.4, we assess the full-sample beta loadings of the same stock (Panel A), bond (Panel B),

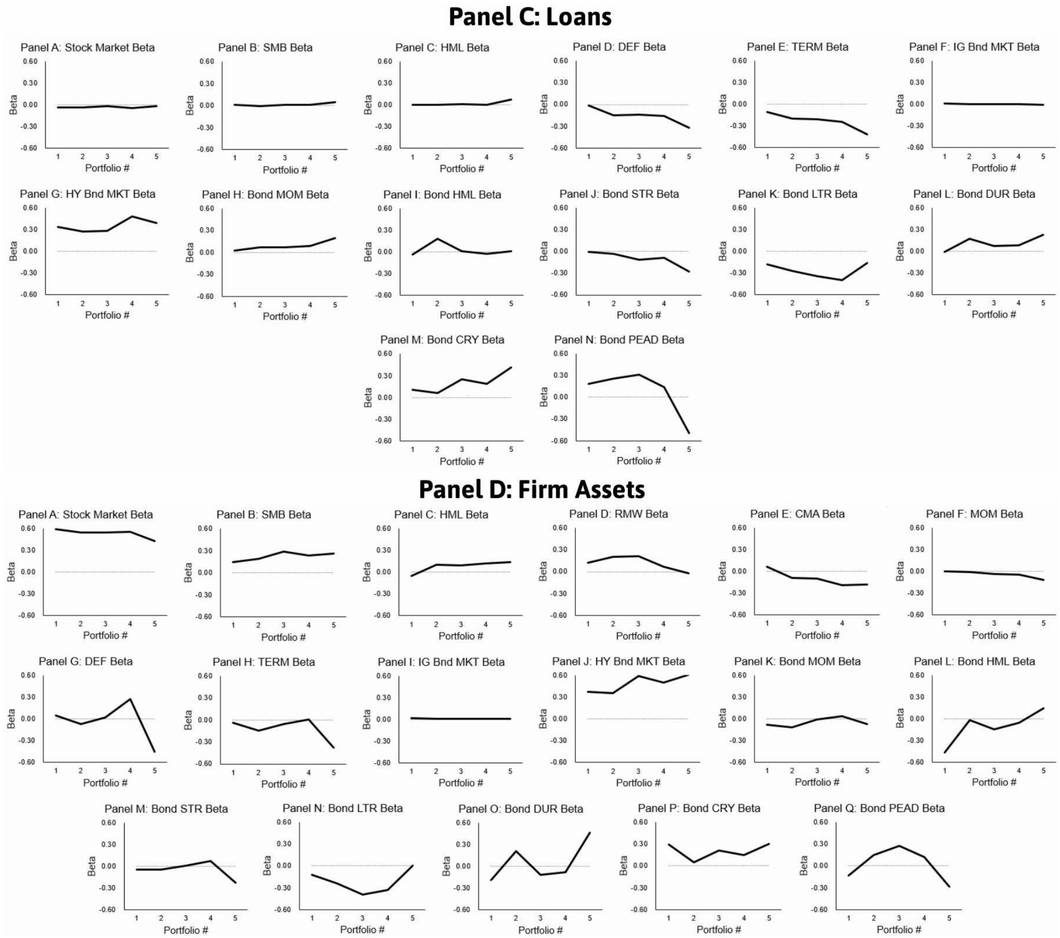


**Figure IA.4: Factor Betas of the Stock-Bond-Loan-Asset Portfolios (continued)**

The figure shows the full-sample betas of the stock (Panel A), firm-specific bond (Panel B), firm-specific loan (Panel C), and firm-specific asset (Panel D) portfolios univariately sorted on distress risk on the FF6S, SB14, SB14, and SB17 factor-model factors, respectively. See Appendix A at the end of the main paper for more details about the construction of the factors included in the FF6S, SB14, and SB17 factor models.

loan (Panel C), and firm-asset (Panel D) distress portfolios on the FF6S, SB14, SB14, and SB17 model factors, respectively. Panels A and B confirm that the stock and bond portfolios attract similar beta relations across the stock-bond and the stock-bond-loan-asset samples. Noteworthy exceptions for the stock portfolios are that the RMW beta is now, surprisingly, more inverted U-shaped (rather than declining) over the portfolios, while the MOM beta is now more declining (rather than flat) over them. Conversely, a noteworthy exception for the bond portfolios is that the TERM beta is more flat (rather than declining) over the portfolios. In agreement with the insight that both bonds and loans constitute debt, Panel C reveals that the loan portfolios often produce similar distress-beta relations as the bond portfolios in Panel B. Different from the bond portfolios, the DEF and TERM betas, however, markedly drop over the loan portfolios, while the duration and carry betas rise over them. Finally, Panel D indicates that the DEF and TERM betas drop over the firm-asset portfolios, while the high-yield bond market, bond HML, and bond duration betas all rise over them.

Using a design and methodology identical to Internet Appendix Table IA.5, Internet Appendix Table IA.8 tabulates the mean returns of the high-minus-low stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) distress spread portfolios in the stock-bond-loan-asset sample separately for each of the twelve months after portfolio formation. Panels A and B suggest that, in contrast to the stock-bond sample, the stock distress premium stays significant for only about 2-3 months after portfolio formation and the bond distress premium for about 1-4 months in that sample. In comparison, the loan distress premium in Panel C continues to be significant for about 3-6 months after portfolio formation and the firm-asset distress premium in Panel D for about 2-3 months. Surprisingly, the equally-weighted portfolios and FM regressions now yield distress premiums staying significant for less long than the value-weighted portfolios. As always, the standard and BGN bond and loan returns produce close-to-identical results. As we discuss in greater detail in our main paper, the weaker persistence of the distress premiums in the stock-bond-loan-asset sample is plausibly driven by that sample being tilted toward larger firms (as they are more likely to own traded loans), and the evidence that larger firms produce weaker asset pricing anomalies (see Fama and French (2008)).

## IA.5 Robustness Tests on the Pricing of Distress Risk

In this section, we run several robustness tests on the pricing of corporate distress risk in stocks, bonds, loans, and firm assets. We first assess the effects of matrix prices on our conclusions. We then look into whether controlling for illiquidity and/or liquidity risk alters those conclusions. We next evaluate the effects of unidentified changes in bond and loan ownership spurred by M&A deals. We finally scrutinize how well our stock, bond, and loan replication strategy in Equation (3) in our main paper is able to capture true (unlevered) asset returns, paying particular attention to the underweighting of loans in that strategy and the omission of non-traded liabilities, such as trade credit.

### IA.5.1. The Effects of Matrix Prices

We start off with looking into the concern that our stock-bond and stock-bond-loan-asset samples contain bond returns calculated from matrix prices because a subset of the Lehman Brothers and Datastream and all of the ICE prices are such prices. Yet, since matrix prices are often stale and/or of a notoriously poor quality, their inclusion in our empirical work may distort our results. To verify that our results are robust, we repeat all portfolio sorts and FM regressions on the pricing of distress risk based on data exclusively featuring bond returns calculated from transaction prices. As TRACE is the only bond price database featuring a comprehensive set of bond transaction prices (recall that NAIC covers only the transaction prices of trades made by insurance firms), we can run this robustness test only on the TRACE sample period from July 2002 to December 2020.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.9 to IA.12 present our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample including only bond returns calculated from TRACE transaction prices. The tables confirm that omitting matrix prices and focusing on a more recent sample period do not materially alter our conclusions. Specifically, mean bond, loan, and asset returns continue to decline significantly with distress risk in all but one single regression (see the loans-with-stocks regression in column (7) of Table IA.12). For example, the monthly standard-return SB14 alpha drops by 0.53% ($t$-statistic: –5.80) over the value-weighted bond deciles in the stock-bond sample (see column (1) in Panel A of Table IA.9). The same alpha drops by 0.26% ($t$-statistic: –2.10) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (1) in Panel C.1 in Table IA.11). Finally, while *LowDistress* yields an insignificant monthly premium of 0.14% in the FM regression explaining standard firm-asset returns in the stock-bond-loan-asset sample, the corresponding number for *HighDistress* is –0.87% ($t$-statistic: –4.18; see column (8) of Table IA.12).

### IA.5.2. The Effects of Illiquidity and Liquidity Risk

We next address the concern that we do not control for bond illiquidity and liquidity risk in our main tests. This concern is particularly valid as distress risk is positively related to the proxies for these factors advocated in Bao et al. (2011) and Lin et al. (2011; recall Internet Appendix Tables IA.4 and IA.7), and the same authors find that mean bond returns rise with both proxies. The reason that we do not control for the proxies in our main tests is that we require daily bond-price data to calculate them, and that only the TRACE database contains such data over the shorter sample period from July 2002 to December 2020. Notwithstanding, we next verify that our results are not driven by illiquidity and liquidity risk by repeating our portfolio sorts and FM regressions on the pricing of distress risk controlling for the two proxies over the shorter sample period.

We follow Bao et al. (2011) and Lin et al. (2011) in computing their bond illiquidity and liquidity risk proxies, respectively. More specifically, the bond illiquidity proxy is a bond's daily-price-change autocovariance over the prior month. Conversely, we calculate the liquidity risk proxy by first running bond-specific regressions of the one-day-ahead excess bond return on its contemporaneous counterpart and signed daily trading volume over the prior month and interpret the coefficient on the volume variable as a proxy for the bond's illiquidity. We then form the monthly change in the cross-sectional average of that coefficient and orthogonalize it with respect to its one-month lagged value and the one-month lagged (scaled) cross-sectional average. We finally run bond-specific regressions of the monthly excess return on the Fama and French (1993) five-factor-model factors (i.e., MKT, SMB, HML, DEF, and TERM) and the orthogonalized change in the cross-sectional average over the prior five years of data, using the coefficient on the orthogonalized change as the liquidity beta.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.9 to IA.12 offer our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample controlling for illiquidity and liquidity risk. While the portfolio sorts control for liquidity risk by adding the return on a spread portfolio based on Pástor and Stambaugh's (2003) stock or Bao et al. (2011) bond illiquidity proxy to the most comprehensive factor model for an asset class, the FM regressions directly add Bao et al.'s (2011) and Lin et al.'s

(2011) proxies as controls. The tables confirm that controlling for illiquidity and/or liquidity risk does not materially alter our conclusions. Specifically, mean stock, bond, loan, and asset returns continue to decline significantly with distress risk in all but the stock sorts in the stock-bond-loan-asset sample (see Panel A in Table IA.11). For example, the monthly standard-return SB15 alpha drops by 0.52% ($t$-statistic: –5.69) over the value-weighted bond deciles in the stock-bond sample (see column (2) in Panel A of Table IA.9). The same alpha drops by 0.28% ($t$-statistic: –2.23) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (2) in Panel C.1 in Table IA.11). Interestingly, while the liquidity proxies are, in line with the literature, often positively related to bond returns in the FM regressions, they never attract statistical significance, presumably due to the comprehensive set of other controls used in our bond regressions.

### IA.5.3. The Effects of M&A-Induced Bond and Loan Ownership Changes

We now examine the effects of unidentified changes in bond and/or loan ownership triggered by M&As on our conclusions about the pricing of distress risk. We use Christian Stolborg's pre-TRACE and WRDS's CRSP-TRACE link files to match our bond and firm data and Michael Roberts's Dealscan-Compustat link file to match our loan and firm data. Using Christian Stolborg's and WRDS's link files is problematic since the files use the ticker as main firm identifier and, as tickers can be asynchronously updated in the bond and firm data, keep only the link with the longest duration, inducing them to miss out on changes in bond ownership after M&As.[8] Conversely, using Michael Roberts's link file is problematic since it matches loans and firms only on the loan origination date.

We rely on the insight from several M&A practitioner books, such as Hooke (2014), that acquiring firms either pay off or assume the (private and public) debt of the target to correctly identify changes in bond and loan ownership after M&As. To be more specific, we follow Choi (2013) and Choi and

[8]Consider the following example. The company with ticker ABC issued bonds with CUSIP XXX and maturity year 2020 in 2008. In 2018, the company with ticker DEF takes over the company with ticker ABC (so that the company with ticker ABC ceases to exist) and assumes the bonds with CUSIP XXX. As both the bond and firm databases timely update the company ticker, the bond issue will be correctly matched with its original owner over the 2008-2017 period and its new owner over the 2018-2020 period. Yet, as the link files only keep the bond-firm match with the longest duration, they keep only the match over the 2008-2017 but not the one over the 2018-2020 period, to address concern that the latter link is spurious. We thank the WRDS support team for explaining that issue to us.

Richardson (2016) in using the CRSP event file to determine all M&A deals and their corresponding dates in which our sample firms were involved, excluding those after which the acquiror does not fully own the target (as, e.g., acquisitions of assets). We next check whether the outstanding bonds and traded loans of the target continue to be traded for at least one year after the M&A deal. If they are, we posit that the acquiror has assumed those bonds and loans and reassign them to the acquiror on the M&A date. Doing so, we identify about 2,900 single bonds in the stock-bond sample which continue to be traded after an M&A, but no more than 13 traded loans in the stock-bond-loan-asset sample. Manually verifying 20 bonds, our strategy can consistently correctly identify the owner of the bonds.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.13 to IA.16 offer our results from the portfolio sorts and the FM regressions on distress risk in the stock-bond and stock-bond-loan-asset sample using bond and loan data accounting for changes in ownership spurred by M&As. The tables demonstrate that accounting for such changes does not materially alter our conclusions, with mean bond, loan, and firm-asset returns still decreasing with distress risk. For example, the monthly standard-return SB14 alpha drops by 0.47% ($t$-statistic: –7.66) over the value-weighted bond deciles in the stock-bond sample (see column (1) in Table IA.13). The same alpha drops by 0.37% ($t$-statistic: –3.05) over the value-weighted loan quintiles in the stock-bond-loan-asset sample (see column (2) in Panel A in Table IA.15). Finally, while *LowDistress* yields an insignificant monthly premium of 0.03% in the FM regression explaining standard firm-asset returns in the stock-bond-loan-asset sample, the corresponding number for *HighDistress* is a much more significant –0.76% ($t$-statistic: –2.98; see column (5) of Table IA.16).

### IA.5.4. The Effects of Omitted and/or Underweighted Asset Classes

We finally consider the effects of inaccuracies in our asset returns calculated from Equation (3) in our main paper on our conclusions about the pricing of distress risk. There are two obvious sources for such inaccuracies. First, the equation omits possibly important non-traded liabilities, such as trade credit, income taxes payable, and non-controlling interests, as well as traded equities not covered by standard databases, such as preferred stock. Second, the equation underweights loans

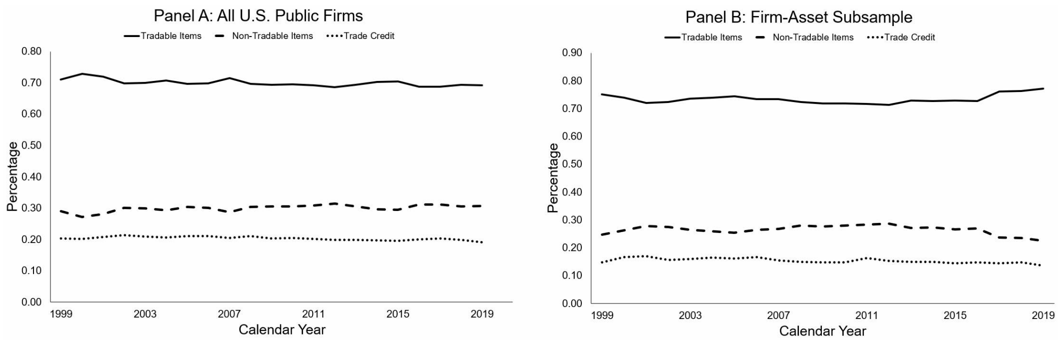


**Figure IA.5: The Proportion of Tradable Equity and Liability Claims**

The figure plots the proportions of tradable (solid line) and non-tradable (broken line) equity and liability claims and trade credit (dotted line) for all Compustat (Panel A) and our stock-bond-loan-asset sample (Panel B) firms over the stock-bond-loan-asset sample period (1999-2020). The tradable claims include debt in current liabilities, long-term debt, and common equity. The non-tradable include accounts payable, income taxes payable, current other liabilities, deferred taxes and investment tax credits, noncontrolling other long-term liabilities, long-term other liabilities, and preferred equity. We include preferred equity among the non-tradable claims since it is not covered in standard data sources (as, e.g., CRSP). Trade credit is accounts payable plus 60% of short-term other liabilities.

since, even for firms with traded loans, those only make up some fraction of all their loans.

We rely on Compustat and Capital IQ data to find out whether our asset return calculations omit important non-traded and/or non-covered equities and liabilities. Starting with the Compustat data, Table IA.17 gives the mean proportions of short-term liabilities (first subpanel), long-term liabilities (second), and equities (third) for the entire Compustat universe (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999-2020 sample period. We first calculate the means by fiscal year and then average over time. The short-term liabilities are accounts payable, debt in current liabilities, income taxes payable, and other such liabilities. We add accrued expenses, a component of other short-term liabilities. The long-term liabilities are long-term debt, deferred taxes and investment tax credits, noncontrolling interests, and other such liabilities. We add capitalized leases, a component of long-term debt. The equities are common and preferred equity.

Assuming that debt in current liabilities, long-term debt, and common equity are all tradable and covered by standard databases, the table suggests that our asset return calculations capture between 70-75% of the average firm's financing sources. Strikingly, income taxes payable, capitalized leases, deferred taxes plus investment tax credits, and non-controlling interests make up an only small proportion of liabilities for the vast majority of firms, with even their 95th percentiles never exceeding 8%. We reach the same conclusion in case of preferred equity, which, although tradable, is not included in CRSP. Conversely, the single important non-traded liability is trade credit, calculated as accounts payable plus accrued expenses[9] and making up between 12-15% of the book value of the average firm's financing sources. Plotting the cross-sectional mean proportions of traded-and-covered sources, non-traded-and/or-non-convered sources, and trade credit over the 1999-2020 sample period, Figure IA.5 corroborates that these proportions are extremely stable over time.

Switching to the Capital IQ data to learn more about the liability structure of our sample firms, Table IA.18 presents the mean proportions of commercial paper, revolving credit lines, term loans, senior bonds, subordinated bonds, capital leases, trust preferred funds, other borrowing, and the residual adjustment[10] for the entire Capital IQ universe (Panel A) and our stock-bond-loan-asset subsample (Panel B) over the 1999-2020 sample period. Assuming that revolving credit lines, term loans, and senior and subordinated bonds are tradable, the table insinuates that our asset return calculations capture between 83% (full sample) and 93% (stock-bond-loan-asset subsample) of the average firm's book value of liabilities. In other words, non-traded liabilities such as commercial paper, capital leases, trust preferred funds, general other borrowing, and the residual adjustment make up an only negligible proportion of total liabilities for the vast majority of firms. Interestingly, however, the table also reveals that the book value of loans (revolving credit lines plus term loans) tends to be higher than the book value of bonds (senior plus subordinated bonds) in the stock-bond-loan-asset subsample, directly underlining the concern that loans are underweighted in our asset return calculations (compare with Panels C and D in Figure 1 in our main paper).

We finally present evidence suggesting that the omission of trade credit from and/or the underweighting of loans in our asset return calculations do not distort our conclusions about the pricing

[9]While accounts payable are trade-debt expenses for which a company has already received an invoice, accrued expenses are those for which it has not yet received an invoice but will do so in the future.

[10]As firms are not obliged to report information on the stated debt instruments, the sum of their outstanding balances is not always equal to the total-debt outstanding balance. To account for that discrepancy, Capital IQ uses the residual adjustment term. Notwithstanding, that term is small for the vast majority of firms.

of distress risk. To do so, we exploit arguments in Erens and Hoffmann (2013) and Costello (2019) implying that trade credit must be close to risk-free. Erens and Hoffmann (2013) reason that since a firm's relations with its suppliers are essential for its operations, and since it is usually initially attempted to restructure failed firms in the U.S., the managers of failed U.S. firms (and even the bankruptcy trustees) almost always pay trade creditors. Similarly, Costello (2019) explains that, prior to 2005, U.S. suppliers could claim back goods from a failed firm under Article 2-702 of the Universal Commercial Code if a request is filed within ten days. More crucially, she highlights that the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 significantly improved U.S. suppliers' bargaining position, giving them 45 days to file a claim, allowing them to reclaim the cash value (and not necessarily the sold goods), and awarding them "super-priority rights" (trumping all other claimants including, for example, secured creditors) in bankruptcy proceedings.

Relying on Erens and Hoffmann's (2013) and Costello's (2019) arguments, we create pseudo-market values and returns for trade credit. We first retrieve the nominal balances of a firm's accounts payable and other short-term liabilities from Compustat Quarterly. We then assume a four-month reporting gap and set the trade credit balance to the most recently available sum of the accounts payable and 60% of the other short-term liabilities balances.[11] We subsequently calculate the pseudo-market value of trade credit as its outstanding balance discounted at the current risk-free rate over the average duration of trade credit in Costello (2019), which is about one month. Conversely, we set the return on trade credit equal to the risk-free rate over the next month. Using the pseudo-market values and returns, we calculate alternative asset returns including trade credit, $r^{A(1)}$, from:

$$r_{i,t}^{A(1)} = \left(\frac{E_{i,t-1}}{MV_{i,t-1}^{(1)}}\right) r_{i,t}^{S} + \left(\frac{B_{i,t-1}}{MV_{i,t-1}^{(1)}}\right) r_{i,t}^{BP} + \left(\frac{L_{i,t-1}}{MV_{i,t-1}^{(1)}}\right) r_{i,t}^{LP} + \left(\frac{TC_{i,t-1}}{MV_{i,t-1}^{(1)}}\right) r_{i,t}^{TC}, \tag{IA.1}$$

where $MV^{(1)}$ is the sum of the market values of stocks, bonds, loans, and trade credit, $E+B+L+TC$, $TC$ is the pseudo-market value of trade credit, and $r^{TC}$ is the return on trade credit.

We also take steps toward correcting the downward bias inherent in the loan weights in our asset

[11] We approximate accrued expenses as 60% of other short-term liabilities as many firms do not report those expenses.

return calculations. In particular, we first retrieve data on the outstanding balances of revolving credit lines, term loans, senior bonds, and subordinated bonds from Capital IQ. As before, we assume a four-month reporting gap and then set the bond (loan) balance to the sum of the senior and subordinated bond (revolving credit line and term loan) balances. Assuming that the loan-to-bond outstanding-balance ratio is similar to the corresponding market-value ratio, we next multiply the market value of bonds, $B$, with the outstanding-balance ratio, to infer the implied market value of loans, $L^{(2)}$. We finally create alternative asset returns with adjusted loan weights, $r^{A(2)}$, from:

$$r_{i,t}^{A(2)} = \left( \frac{E_{i,t-1}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^{S} + \left( \frac{B_{i,t-1}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}^{(2)}}{MV_{i,t-1}^{(2)}} \right) r_{i,t}^{LP}, \tag{IA.2}$$

where $MV^{(2)}$ is the sum of the stock, bond, and implied loan values, $E + B + L^{(2)}$.

A downside of the above loan-weight-adjustment strategy is that it requires the existence of bonds in a firm's capital structure to be feasible. As, however, illustrated in Panel C of Figure 1 of our main paper, not all firms with traded loans also own bonds. To address that issue, we also rely on an alternative strategy. In particular, we use Mergent FISD to calculate the aggregate balance of all outstanding bonds of a firm at the end of month $t$. We next subtract that balance from the firm's book value of short plus long-term debt from Compustat to approximate the aggregate balance of all its outstanding loans at that time. Using the firm's book value of equity, its outstanding bond balance, and its outstanding loan balance, we then calculate its stock, bond, and loan weights. We finally calculate its asset return based on those weights, $r^{A(3)}$, from:

$$r_{i,t}^{A(3)} = \left( \frac{E_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^{S} + \left( \frac{B_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^{BP} + \left( \frac{L_{i,t-1}^{(3)}}{MV_{i,t-1}^{(3)}} \right) r_{i,t}^{LP}, \tag{IA.3}$$

where $E^{(3)}$ is book equity, $B^{(3)}$ the outstanding bond balance, $L^{(3)}$ the outstanding loan balance, and $MV^{(3)} = E^{(3)} + B^{(3)} + L^{(3)}$. While Equation (IA.3) can be applied to firms with and without bonds, it relies on book (and not market) values to calculate the asset weights.[12]

[12] In untabulated tests, we also looked into combinations of the trade-credit adjustment and each of the loan-weight adjustments, finding that these combinations yield results in agreement with the single adjustments.

Using designs similar to the corresponding tables in the main paper, Internet Appendix Tables IA.19 to IA.20 present our results from firm-asset portfolio sorts and FM regressions using the original, trade-credit-adjusted, and loan-weight-adjusted asset returns. The tables suggest that the adjustments do not alter our conclusion that mean firm-asset returns are either hump-shaped in or decline with distress risk. Looking into Panel A of Table IA.19, the original SB17 alpha declines by 0.66% ($t$-statistic: –2.71) over the value-weighted standard-return portfolios. In contrast, the trade-credit-adjusted SB17 alpha declines by 0.54% ($t$-statistics: –2.63) over those same portfolios, while the loan-weight-adjusted alphas decline by 0.63% and 0.56% ($t$-statistics: –2.76 and –2.71), respectively. Overall, the changes in the SB17 alpha over the portfolios and their corresponding inference levels are always highly similar across all alternative asset return specifications.

## IA.6 Shareholder Advantage and the Distress Anomaly

While Garlappi et al. (2008) and Garlappi and Yan (2011) propose an alternative explanation for the negative stock distress premium grounded in shareholders' ability to extract rents from debtholders in distress ("shareholder advantage theory"), Avramov et al. (2022) argue that the negative debt distress premiums estimated in their work and ours cast a serious blow to that explanation. To formalize that claim, we use Fan and Sundaresan's (2000) real options model of a stock-and-debt financed firm in which shareholders can strategically default to show that while a higher shareholder advantage does indeed yield a *less* positive stock distress premium, it is unable to produce a negative debt distress premium. We start off with outlining the model's assumptions. We next give the model's closed-form solutions for distress risk and the expected asset, stock, and debt return. We finally follow Garlappi et al. (2008) in using simulations to evaluate how shareholder advantage conditions the relations between distress risk and the expected asset, stock, or debt return in the model.

### IA.6.1. Fan and Sundaresan's (2000) Modelling Assumptions

Let us consider a stock-and-debt financed firm operating over a continuous infinite time horizon indexed by $t \in [0, \infty)$ and exposed to corporate taxes and deadweight costs of bankruptcy. The firm's unlevered value, $V_t$, obeys the geometric Brownian motion (GBM):

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dB_t, \tag{IA.4}$$

where $\mu$ is the expected return of the unlevered assets, $\delta < \mu$ the dividend yield, $\sigma$ the volatility of the unlevered assets, and $dB_t$ the increment of a standard Brownian motion. In each instant, the firm is taxed at a constant rate of $\tau$, creating a tax shield of debt. Upon defaulting, the firm loses the fraction $\alpha$ of its value in direct and/or indirect bankruptcy costs.

The firm is financed through both equity and debt. The debt comes in the form of a perpetuity requiring an instantaneous payment of $c$ per time unit. Importantly, shareholders have the (perpetual) option to strategically default on that debt payment, triggering a renegotiation between them and debtholders about the residual firm value. The outcome of that renegotiation are the fractions of residual firm value awarded to shareholders ($\tilde{\theta}$) and debtholders ($1-\tilde{\theta}$), which are determined through a Nash bargaining game. More specifically, the fraction awarded to shareholders, $\tilde{\theta}$, maximizes the joint benefit to shareholders and debtholders and can be written as:

$$\tilde{\theta} = \text{argmax} \left[\tilde{\theta} v(V) - 0\right]^{\eta} \left[(1-\tilde{\theta})v(V) - (1-\alpha)V\right]^{(1-\eta)} = \eta \left(1 - \frac{(1-\alpha)V}{v(V)}\right), \tag{IA.5}$$

where $v(V)$ is the firm's levered asset value and $\eta$ shareholders' bargaining power. Equation (IA.5) demonstrates that, in line with intuition, the fraction of firm value awarded to shareholders rises with shareholders' bargaining power, $\eta$, and the deadweight costs of bankruptcy, $\alpha$.

### IA.6.2. Model Solutions

In this setup, Fan and Sundaresan (2000) show that the value of the levered assets, $\upsilon(V)$, is:

$$\upsilon(V) = \begin{cases} V + \frac{\tau c}{r} - \frac{\lambda_2}{\lambda_2 - \lambda_1}\frac{\tau c}{r}\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ V + \frac{-\lambda_1}{\lambda_2 - \lambda_1}\frac{\tau c}{r}\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_2} & \text{if } V \leq \tilde{V}_S, \end{cases} \tag{IA.6}$$

where $\tilde{V}_S$, the constant unlevered-asset-value threshold at or below which shareholders optimally strategically default on repaying the outstanding debt, is equal to:

$$\tilde{V}_S = \frac{c(1-\tau+\eta\tau)}{r}\frac{-\lambda_1}{1-\lambda_1}\frac{1}{1-\eta\alpha}, \tag{IA.7}$$

and:

$$\lambda_1 = \left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right) - \sqrt{\left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} < 0, \tag{IA.8}$$

$$\lambda_2 = \left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r-\delta}{\sigma^2}\right)^2 + \frac{2r}{\sigma^2}} > 1. \tag{IA.9}$$

Next, they show that the value of equity, $\tilde{E}(V)$, is equal to:

$$\tilde{E}(V) = \begin{cases} V - \frac{c(1-\tau)}{r} + \left[\frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)}\frac{\tau c}{r}\right]\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} & \text{if } V > \tilde{V}_S, \\ \theta^* \upsilon(V) & \text{if } V \leq \tilde{V}_S, \end{cases} \tag{IA.10}$$

and that the value of debt, $\tilde{D}(V)$, is the levered asset value minus the equity value, $\upsilon(V) - \tilde{E}(V)$.

In turn, Garlappi et al. (2008) establish that the time-0 probability that shareholders strategically default over the period until time $T$, $\text{Prob}_{(0,T]}(V_0)$, is:

$$\text{Pr}_{(0,T]} = N\left(\frac{\ln(\tilde{V}_S) - \ln(V_0) - \gamma T}{\sigma\sqrt{T}}\right) + e^{\frac{2\gamma(\ln(\tilde{V}_S)-\ln(V_0))}{\sigma^2}} N\left(\frac{\ln(\tilde{V}_S) - \ln(V_0) + \gamma T}{\sigma\sqrt{T}}\right), \tag{IA.11}$$

where $\gamma = \mu - \delta - \frac{1}{2}\sigma^2$, and $N(.)$ is the cumulative standard normal distribution. To calculate the expected stock return over the period until time $t$, $\mathbb{E}_0(\tilde{E}(V_t))/\tilde{E}(V_0)$, they next show that:

$$\begin{aligned}
\mathbb{E}_0(\tilde{E}(V_t)) &= \eta\alpha V_0 e^{(\mu-\delta)t} N\left(h(t)-\sigma\sqrt{t}\right) \\
&- \eta\frac{\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma-\lambda_2)t} N\left(h(t)-\lambda_2\sigma\sqrt{t}\right) \\
&+ V_0 e^{(\mu-\delta)t} N\left(-h(t)+\sigma\sqrt{t}\right) - \frac{c(1-\tau)}{r} N\left(-h(t)\right) \\
&+ \left[\frac{c(1-\tau)}{(1-\lambda_1)r} - \frac{\lambda_1(1-\lambda_2)\eta}{(\lambda_2-\lambda_1)(1-\lambda_1)}\frac{\tau c}{r}\right]\left(\frac{V}{\tilde{V}_S}\right)^{\lambda_1} \\
&\times e^{\lambda_1(\gamma-\lambda_1)t} N\left(-h(t)+\lambda_1\sigma\sqrt{t}\right), \qquad \text{(IA.12)}
\end{aligned}$$

where $h(t) = \frac{\ln(\tilde{V}_S/V_0)-\gamma t}{\sigma\sqrt{t}}$, and then scale that with the equity value in Equation (IA.10), $\tilde{E}(V_0)$.

We finally use techniques analogous to Garlappi et al. (2008) to also derive the expected debt return over the period until time $t$, $\mathbb{E}_0(\tilde{D}(V_t))/\tilde{D}(V_0)$. To do so, we first recall that the value of debt is the value of the levered assets minus the equity value (i.e., $\tilde{D}(V) = \upsilon(V) - \tilde{E}(V)$). We can thus calculate $\mathbb{E}_0(\tilde{D}(V_t))$ from the time-0 expectation of the levered asset value at time $t$, $\mathbb{E}_0(\upsilon(V_t))$. To form the levered-asset-value expectation, we write the unlevered asset value at time $t$ as:

$$V_t = V_0 e^{(\mu-\delta-\frac{1}{2}\sigma^2)t+\sigma(B_t-B_0)}, \qquad \text{(IA.13)}$$

which is log-normally distributed with $E[\ln V_t] = \ln V_0 + \gamma t$ and $\mathrm{Var}[\ln V_t] = \sigma^2 t$. We next consider the integral $\int_0^a V_t^b p(V_t)dV_t$, where $a$ and $b$ are constants and $p(V_t)$ is the probability density function of the log-normal variable $V_t$. Plugging in for $p(V_t)$, we obtain the equality:

$$\int_0^a V_t^b p(V_t)dV_t = \int_0^a V_t^b \frac{1}{\sqrt{2\pi\sigma^2 t}V_t} e^{-\frac{1}{2}\left(\frac{\ln V_t-(\ln V_0+\gamma t)}{\sigma\sqrt{t}}\right)^2} dV_t. \qquad \text{(IA.14)}$$

Using the change of variable $X_t = \frac{\ln V_t - \ln V_0 - \gamma t}{\sigma\sqrt{t}}$, the right-hand side of Equation (IA.14) becomes:

$$\begin{aligned}
& \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} e^{b(\ln V_0+\gamma t+\sigma\sqrt{t}X_t)} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2} dX_t & \text{(IA.15)} \\
= \;& V_0^b e^{b\gamma t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}X_t^2+b\sigma\sqrt{t}X_t-\frac{1}{2}b^2\sigma^2 t+\frac{1}{2}b^2\sigma^2 t} dX_t & \text{(IA.16)} \\
= \;& V_0^b e^{b\gamma t+\frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t^2-2b\sigma\sqrt{t}X_t+b^2\sigma^2 t)} dX_t & \text{(IA.17)} \\
= \;& V_0^b e^{b\gamma t+\frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(X_t-b\sigma\sqrt{t})^2} dX_t. & \text{(IA.18)}
\end{aligned}$$

Using the change of variable $Y_t = X_t - b\sigma\sqrt{t}$, we can write expression (IA.18) as:

$$\begin{aligned}
& V_0^b e^{b\gamma t+\frac{1}{2}b^2\sigma^2 t} \int_{-\infty}^{\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}}-b\sigma\sqrt{t}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}Y_t^2} dY_t & \text{(IA.19)} \\
= \;& V_0^b e^{b\gamma t+\frac{1}{2}b^2\sigma^2 t} N\left(\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}} - b\sigma\sqrt{t}\right). & \text{(IA.20)}
\end{aligned}$$

Relying on identical techniques, we can also show that:

$$\int_a^{\infty} V_t^b p(V_t) dV_t = V_0^b e^{b\gamma t+\frac{1}{2}b^2\sigma^2 t} N\left(-\frac{\ln(a/V_0)-\gamma t}{\sigma\sqrt{t}} + b\sigma\sqrt{t}\right). \tag{IA.21}$$

Using Equation (IA.6), we next write the expected levered asset value at time $t$, $\mathbb{E}_0(\upsilon(V_t))$, as:

$$\begin{aligned}
\mathbb{E}_0(\upsilon(V_t)) \;=\;& \int_0^{\infty} V_t p(V_t) dV_t + \int_{\tilde{V}_S}^{\infty} \frac{\tau c}{r} p(V_t) dV_t - \int_{\tilde{V}_S}^{\infty} \frac{\lambda_2}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_1} p(V_t) dV_t \\
+\;& \int_0^{\tilde{V}_S} \frac{-\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_t}{\tilde{V}_S}\right)^{\lambda_2} p(V_t) dV_t \\
=\;& \int_0^{\infty} V_t p(V_t) dV_t + \frac{\tau c}{r}\int_{\tilde{V}_S}^{\infty} p(V_t) dV_t - \frac{\lambda_2}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{1}{\tilde{V}_S}\right)^{\lambda_1} \int_{\tilde{V}_S}^{\infty} V_t^{\lambda_1} p(V_t) dV_t \\
+\;& \frac{-\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{1}{\tilde{V}_S}\right)^{\lambda_2} \int_0^{\tilde{V}_S} V_t^{\lambda_2} p(V_t) dV_t. \qquad \text{(IA.22)}
\end{aligned}$$

Exploiting the closed-form solutions for the integrals $\int_0^a V_t^b p(V_t) dV_t$ and $\int_a^{\infty} V_t^b p(V_t) dV_t$ in Equations (IA.20) and (IA.21), respectively, we finally write Equation (IA.22) as:

$$\begin{aligned}
\mathbb{E}_0(\upsilon(V_t)) &= V_0 e^{(\mu-\delta)t} + \frac{\tau c}{r} N\left(-h(t)\right) \\
&- \frac{\lambda_2}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_1} e^{\lambda_1(\gamma+\frac{1}{2}\lambda_1\sigma^2)t} N\left(-h(t)+\lambda_1\sigma\sqrt{t}\right) \\
&+ \frac{-\lambda_1}{\lambda_2-\lambda_1}\frac{\tau c}{r}\left(\frac{V_0}{\tilde{V}_S}\right)^{\lambda_2} e^{\lambda_2(\gamma+\frac{1}{2}\lambda_2\sigma^2)t} N\left(h(t)-\lambda_2\sigma\sqrt{t}\right). \qquad \text{(IA.23)}
\end{aligned}$$

Subtracting the time-0 expectation of the equity value in Equation (IA.12) from the time-0 expectation of the levered asset value in Equation (IA.23), we obtain the time-0 expectation of the debt value (i.e., $\mathbb{E}_0(\tilde{D}(V_t)) = \mathbb{E}_0(\upsilon(V_t)) - \mathbb{E}_0(\tilde{E}(V_t))$). Scaling the time-0 debt-value expectation with the current debt value, which is the current levered asset value in Equation (IA.6) minus the current equity value in Equation (IA.10), we obtain the expected debt return from time 0 to $t$.

### IA.6.3. Shareholder Advantage and Expected Returns

We finally follow Garlappi et al. (2008) in using simulations to find out how shareholder advantage affects the relations between default risk and expected asset, stock, and debt returns in the model. To that end, we generate a cross-section of 100,000 artificial firms. We calculate each firm's default risk over the period from $t = 0$ to 1 from Equation (IA.11) and its three expected returns over the period from $t = 0$ to $1/12$ from Equations (IA.6), (IA.10), (IA.12), and (IA.23). Consistent with Garlappi et al. (2008), we set the riskfree rate of return, $r$, to 0.04 per annum, the payout rate, $\delta$, to 0.04, the tax rate, $\tau$, to 0.35, and the bankruptcy cost, $\alpha$, to 0.50. Also in line with them, we draw the coupon rate, $c$, the expected unlevered asset return, $\mu$, and the initial unlevered asset value, $V_0$, from uniform distributions with support $[0.05, 0.10]$, $[\delta + \frac{1}{2}\sigma, 3(\delta + \frac{1}{2}\sigma)]$, and $[V_S, V_S + 1.25]$, respectively. Since, unlike them, we do not have access to the asset volatility estimates from Moody's KMV Corporation, we also draw the asset volatility, $\sigma$, from a uniform distribution with support $[0.10, 0.30]$. We finally set the shareholder bargaining power parameter $\eta$ to either 0.20, 0.50, or 0.80.

Figure IA.6 displays the monthly expected levered-asset (Panel A), stock (Panel B), and debt (Panel C) returns of equally-weighted decile portfolios containing the 100,000 artificial firms and sorted

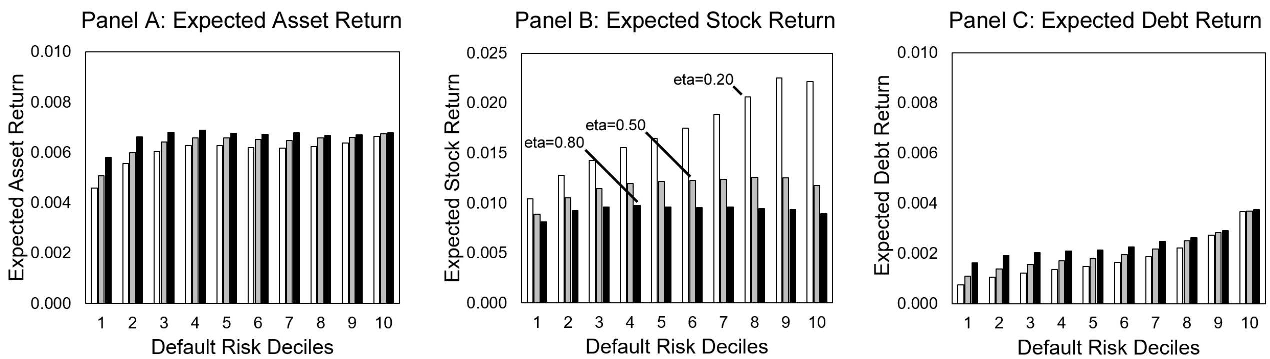


**Figure IA.6: Shareholder Advantage and Expected Asset, Stock, and Debt Returns**

The figure offers the expected levered-asset (Panel A), stock (Panel B), and debt (Panel C) returns of equally-weighted default risk portfolios conditional on a shareholder advantage of 0.20 (white bar), 0.50 (grey), and 0.80 (black).

according to one-year default risk. In agreement with Garlappi et al. (2008), Panel B suggests that a greater shareholder advantage (i.e., a higher $\eta$) creates a less positive and more downward hump-shaped default risk-expected stock return relation. The reason is that shareholders own the levered assets net of coupon payments plus a put option to stop paying coupons and to start negotiations about the firm's residual value. As shareholders' bargaining power increases, the value of the put option rises, especially when default risk is high, and, as the systematic risk of the put option is negative, its greater value drags down the expected stock return. In contrast, as debtholders are short that same put option, and the systematic risk of a short put option is positive, Panel C reveals that a higher shareholder bargaining power creates a more positive default risk-expected debt return relation, at least once we control for expected levered-asset return changes coming from the initial unlevered-asset-value draws depending on the strategic default threshold $V_S$ (see Panel A). Notwithstanding the expected levered-asset return effect, the main lesson to take away from Figure IA.6 is that, independent of shareholders' bargaining power, the default risk-expected debt return relation is always positive. The upshot is that shareholder advantage cannot explain negative distress premiums in debt.

## IA.7 Disinvestment Options and the Distress Anomaly

In Section IV of our main paper, we show that a real options model of a stock-and-debt financed firm with capacity utilization, investment, and disinvestment choices can explain the negative stock and debt distress premiums obtained in our empirical work. In this section of the Internet Appendix, we derive the model's quasi-closed-form solutions for the firm's asset value and its expected asset return. We also offer more details about the Monte Carlo simulations run to derive the firm's equity and debt values and its expected stock and debt returns. We finally give comparative statics for the conclusions about the distress risk-expected return relations derived from the model.

### IA.7.1. Deriving the Asset Value Model Solution

We first derive the model's closed-form solutions for the firm's asset value and its expected asset return. As we stress in our main paper, the firm's asset value is the sum of the values of its incremental options to produce (assets-in-place) and its incremental options to acquire more options to produce (growth options). We use the risk-neutral measure to value all the incremental options. In particular, denoting the value of the incremental option on asset increment $k$ (either an asset-in-place or growth option) by $\Delta C(\theta; k)$, the definition of the risk-neutral measure gives us:

$$E^{\mathbb{Q}}\left[\frac{d\Delta C(\theta; k) + \pi(\theta; k)dt}{\Delta C(\theta; k)}\right] = rdt, \tag{IA.24}$$

where $E^{\mathbb{Q}}[.]$ is an expectation under the equivalent martingale measure and $\pi(\theta; k)$ is the one-time-unit cash flow paid out by the incremental option in the current instant. Intuitively, Equation (IA.24) states that the expected return of any asset under the risk-neutral measure is equal to the risk-free rate of return. Using Itô's lemma, simplifying, and rearranging, we obtain:

$$\frac{1}{2}\sigma^2\theta^2\frac{\partial^2\Delta C(\theta; k)}{\partial\theta^2} + (r-\delta)\theta\frac{\partial\Delta C(\theta; k)}{\partial\theta} - r\Delta C(\theta; k) + \pi(\theta; k) = 0, \tag{IA.25}$$

which the value of the incremental option has to fulfill subject to boundary conditions.

Dealing with the valuation of the assets-in-place first, we need to separately consider the cases in which (i) the firm first switches off an option to produce and then sells it and in which (ii) it sells off the switched-on option to produce. Starting with the first case, the firm optimally switches on the option to produce the $k$th output increment when the output price exceeds its variable cost, that is, when $\theta \geq c_1 + c_2 k$ (see Section B in our main paper). In this case, it is well-known that the value of this incremental option, $\Delta V(\theta; k)$, is of the general form:

$$\Delta V(\theta; k) = A_O \theta^{\beta_1} + B_O \theta^{\beta_2} + \frac{\theta}{\delta} - \frac{c_1 + c_2 k + f}{r}, \tag{IA.26}$$

where $A_O$ and $B_O$ are free parameters, and:

$$\beta_1 = \frac{1}{2} - (r - \delta)/\sigma^2 + \sqrt{\left[(r - \delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} > 1, \tag{IA.27}$$

$$\beta_2 = \frac{1}{2} - (r - \delta)/\sigma^2 - \sqrt{\left[(r - \delta)/\sigma^2 - \frac{1}{2}\right]^2 + 2r/\sigma^2} < 0. \tag{IA.28}$$

Since $\lim_{\theta \to +\infty} \Delta V(\theta; k)$ is equal to $\frac{\theta}{\delta} - \frac{c_1 + c_2 k + f}{r}$, we immediately have $A_O = 0$. Conversely, when $\theta^D \leq \theta < c_1 + c_2 k$, where $\theta^D$ is the disinvestment output-price threshold, the firm optimally switches off the option. In this case, the value of the option is of the general form:

$$\Delta V(\theta; k) = A_I \theta^{\beta_1} + B_I \theta^{\beta_2} - \frac{f}{r}, \tag{IA.29}$$

where $A_I$ and $B_I$ are free parameters. Finally, when the output price drops below $\theta^D$, that is, when $\theta \leq \theta^D < c_1 + c_2 k$, the value of the option is equal to the disinvestment proceeds $S$.

To find the values of $A_I$, $B_I$, $B_O$, and $\theta^D$, we ensure that the three component solutions value-match with and smooth-paste into another. In particular, we require that:

$$B_O(\theta^P)^{\beta_2} + \frac{(\theta^P)}{\delta} - \frac{c_1 + c_2 k + f}{r} = A_I(\theta^P)^{\beta_1} + B_I(\theta^P)^{\beta_2} - \frac{f}{r}, \tag{IA.30}$$

$$B_O \beta_2 (\theta^P)^{\beta_2 - 1} + \frac{1}{\delta} = A_I \beta_1 (\theta^P)^{\beta_1 - 1} + B_I \beta_2 (\theta^P)^{\beta_2 - 1}, \tag{IA.31}$$

$$A_I(\theta^D)^{\beta_1} + B_I(\theta^D)^{\beta_2} - \frac{f}{r} = S, \tag{IA.32}$$

$$A_I \beta_1 (\theta^D)^{\beta_1 - 1} + B_I \beta_2 (\theta^D)^{\beta_2 - 1} = 0, \tag{IA.33}$$

where $\theta^P \equiv c_1 + c_2 k$. Equation (IA.30) ensures that the values of the switched-on and switched-off options are identical at the optimal switching threshold $\theta^P$, while Equation (IA.31) ensures that their partial derivatives with respect to the output price are also identical at that point. Conversely, Equation (IA.32) ensures that the value of the switched-off option is equal to the disinvestment proceeds at the disinvestment threshold $\theta^D$, while Equation (IA.33) ensures that the partial derivative of that option's value with respect to the output price is equal to zero at that point.

Solving for $A_I$, $B_O - B_I$, $B_I$, and $\theta^D$, we obtain:

$$A_I = \left(\frac{r - \beta_2(r - \delta)}{r\delta(\beta_1 - \beta_2)}\right)(\theta^P)^{1-\beta_1}, \tag{IA.34}$$

$$B_O - B_I = \left(\frac{r - \beta_1(r - \delta)}{r\delta(\beta_1 - \beta_2)}\right)(\theta^P)^{1-\beta_2}, \tag{IA.35}$$

$$B_I = \frac{S + f/r}{1 - \beta_2/\beta_1}(\theta^D)^{-\beta_2}, \tag{IA.36}$$

$$\theta^D = \left(\left(\frac{1}{A_I}\right)\left(\frac{S + f/r}{1 - \beta_1/\beta_2}\right)\right)^{1/\beta_1}. \tag{IA.37}$$

We use Equation (IA.34) to calculate $A_I$. We plug $A_I$ into Equation (IA.37) to calculate $\theta^D$. We next plug $\theta^D$ into Equation (IA.36) to calculate $B_I$. We finally use Equation (IA.35) to calculate $B_O$.

Turning to the second case in which the firm optimally sells the switched-on option, the general form of the value of the option is still given by Equation (IA.26) when $\theta \geq \theta^D$. Also, its value is still equal to the disinvestment proceeds $S$ when $\theta < \theta^D$. To find the values of $B_O$ and $\theta^D$ in this case, we ensure that the component solutions value-match with and smooth-paste into another:

$$B_O(\theta^D)^{\beta_2} + \frac{(\theta^D)}{\delta} - \frac{c_1 + c_2 k + f}{r} = S, \tag{IA.38}$$

$$B_O \beta_2 (\theta^D)^{\beta_2 - 1} + \frac{1}{\delta} = 0, \tag{IA.39}$$

where Equation (IA.38) ensures that the value of the switched-on option is equal to the disinvestment proceeds at the disinvestment threshold, while Equation (IA.39) ensures that its partial derivative with respect to the output price is zero at that point. Solving for $B_O$ and $\theta^D$, we obtain:

$$B_O = -\frac{1}{\delta\beta_2}(\theta^D)^{1-\beta_2}, \tag{IA.40}$$

$$\theta^D = \frac{\delta\beta_2(S + (c_1 + c_2 k + f)/r)}{\beta_2 - 1}. \tag{IA.41}$$

We use Equation (IA.41) to calculate $\theta^D$ and then plug $\theta^D$ into Equation (IA.40) to obtain $B_O$.

In practice, we always start with the first case. If we then notice that the first case gives us a contradiction (i.e., if we find that $\theta^D > c_1 + c_2 k$), we move on to the second case.

We next value the firm's growth options. Recalling the well-known insight that a perpetual call option whose value depends only on some stochastic variable is optimally exercised once the stochastic variable hits some threshold from below, we can write the pre-exercise value of the option to acquire the option to produce the $k$th output increment, $G(\theta; k)$, as:

$$\Delta G(\theta; k) = G\theta^{\beta_1} + H\theta^{\beta_2}, \tag{IA.42}$$

where $G$ and $H$ are free parameters. Since $\lim_{\theta \to 0} \Delta G(\theta; k) = 0$, we immediately have $H = 0$. In contrast, its value upon an exercise is simply: $\Delta G(\theta; k) = \Delta V(\theta; k) - I$.

To find the values of $G$ and $\theta^*$, the optimal exercise threshold, we ensure that the two component solutions value-match with and smooth-paste into another. In particular, we require that:

$$B_O(\theta^*)^{\beta_2} + \frac{(\theta^*)}{\delta} - \frac{c_1 + c_2 k + f}{r} - I \quad = \quad G(\theta^*)^{\beta_1}, \tag{IA.43}$$

$$B_O \beta_2 (\theta^*)^{\beta_2 - 1} + \frac{1}{\delta} \quad = \quad G\beta_1(\theta^*)^{\beta_1 - 1}, \tag{IA.44}$$

where Equation (IA.43) ensures that the value of the growth option is equal to its exercise payoff (i.e., the value of the corresponding option to produce minus the investment cost) at the optimal investment threshold, whereas Equation (IA.44) ensures that the partial derivatives of the option's value and its early exercise payoff are identical at that point. Solving Equation (IA.44) for $G$, we obtain:

$$G = \frac{1}{\beta_1} B_O(\theta^*)^{\beta_2 - \beta_1} + \frac{(\theta^*)^{1-\beta_1}}{\beta_1 \delta}. \tag{IA.45}$$

Substituting $G$ into Equation (IA.43), we then numerically solve for $\theta^*$.

### IA.7.2. Using Monte Carlo Simulations to Derive the Equity and Debt Values

We use Monte Carlo simulations to evaluate the discounted risk-neutral expectation identifying a firm's debt value, $D(\theta; T)$, as we are unable to solve that expectation in closed-form (recall Equation (10) in our main paper). More specifically, we vary the initial output price, $\theta$, from 0.10 to 2.00 to create 100,000 daily sample output-price paths for each initial output price under the risk-neutral measure $\mathbb{Q}$. For each single path, we next determine the firm's optimal capacity utilization, expansion, and contraction decisions at the end of each day; calculate the sum of compounded-up disinvestment proceeds at time $T$, $S_T$; calculate the value of the firm's assets at that same time using the equations in Section IA.7.1., $V(\theta_T)$; and finally calculate $e^{-rT}\min(C, V(\theta_T) + (1-q)S_T)$. Averaging over the 100,000 $e^{-rT}\min(C, V(\theta_T) + (1-q)S_T)$ values, we obtain an approximation of the debt value, $D(\theta; T)$. As the equity value is the asset minus the debt value (i.e., $E(\theta; T) = V(\theta; T) - D(\theta; T)$), we also obtain an approximation of the equity value. Repeating those steps using the original initial output price plus or minus 0.0001, we use $(D(\theta + 0.0001; T) - D(\theta - 0.0001; T))/0.0002$ and $(E(\theta + 0.0001; T) - E(\theta - 0.0001; T))/0.0002$ to approximate the partial derivatives of the debt and equity value with

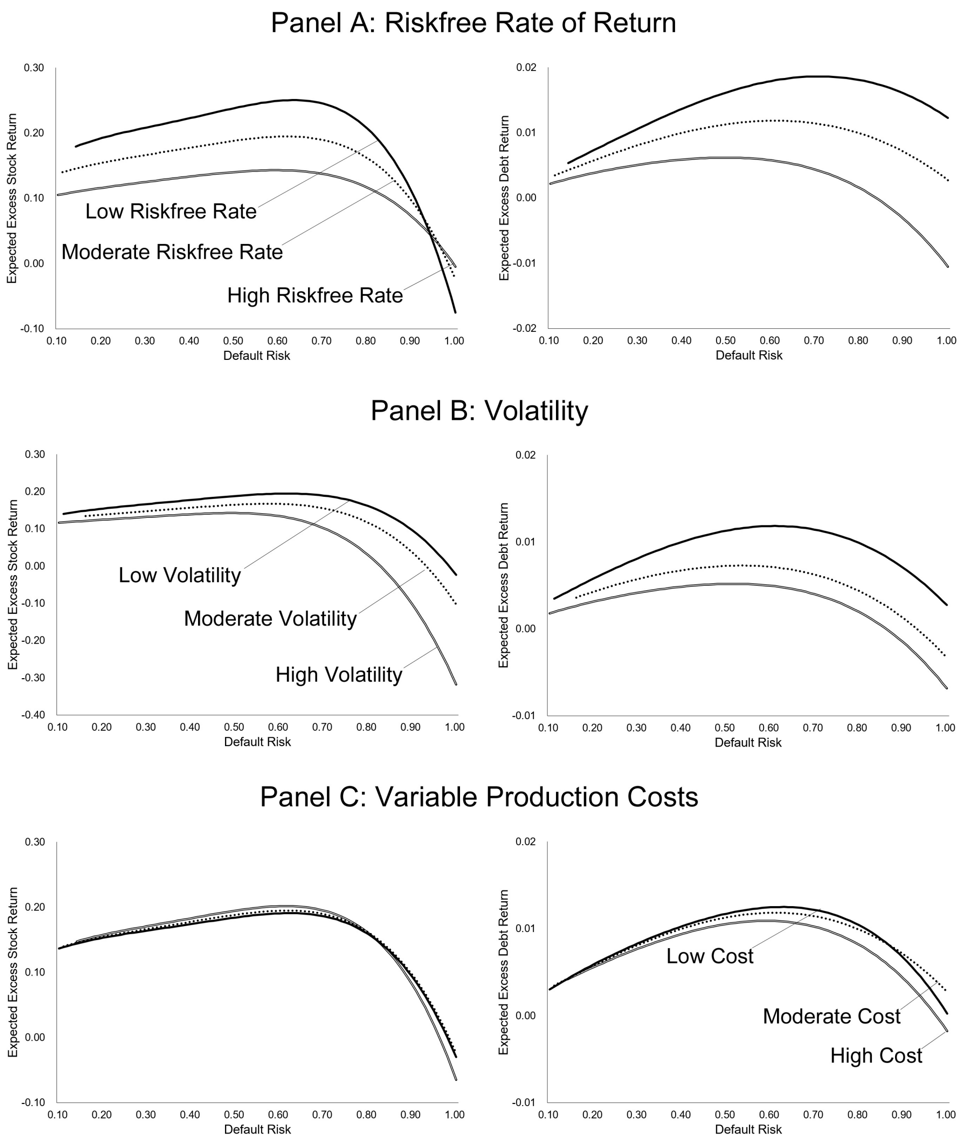


**Figure IA.7: The Default Risk-Expected Return Relations: Comparative Statics**

The figure offers comparative statics on the relations between the expected excess stock (left subpanels) and debt (right subpanels) return and default risk assuming a disinvestment gain, $S$, of eight and a fraction of disinvestment proceeds distributed to shareholders, $q$, equal to 0.10. In Panels A to F, we separately vary the riskfree rate of return $r$, output price volatility $\sigma$, variable production costs $c_2$, fixed production costs $f$, the coupon payment $C$, and the time-to-maturity $T$, respectively. See Section D in our main paper for more details about our basecase parameter value choices and Section IA.7.3. in this Internet Appendix for the high and low values.

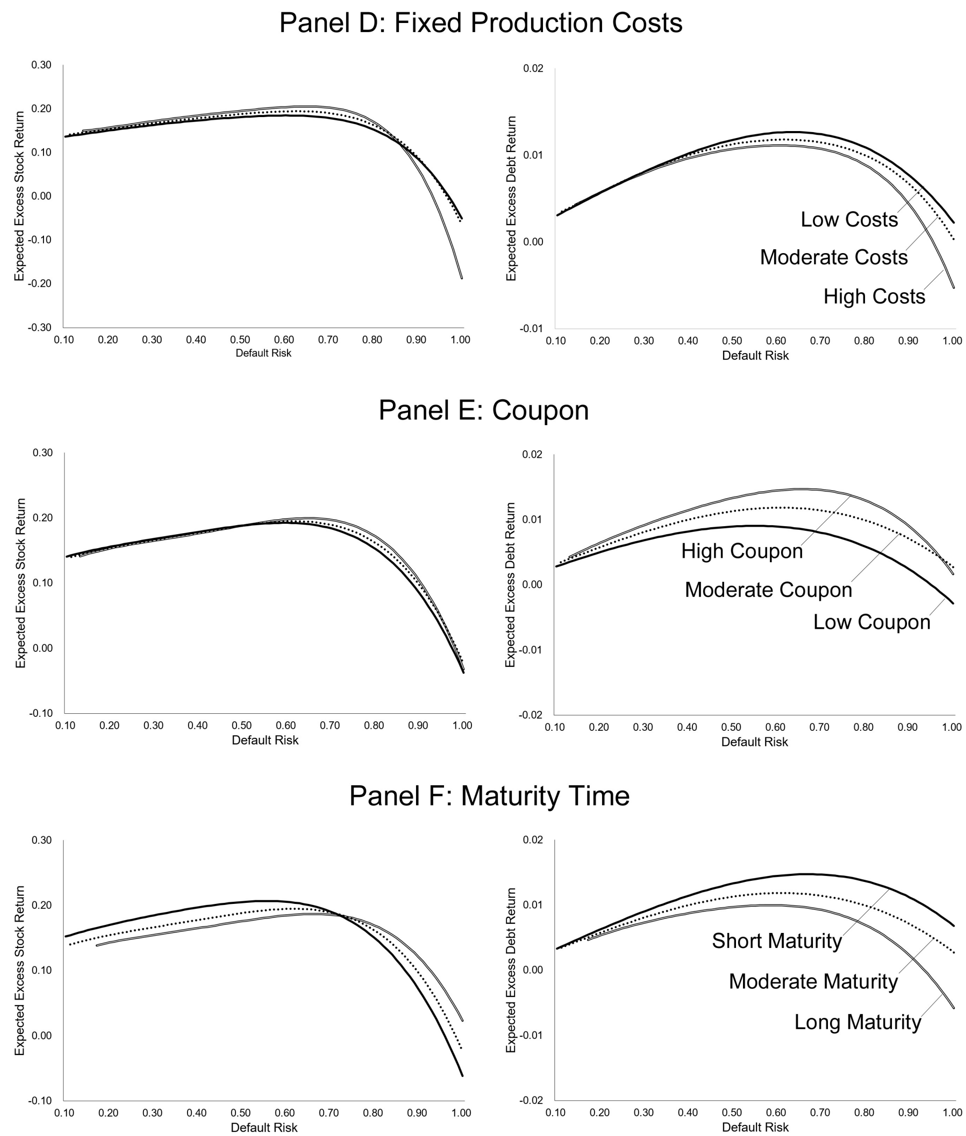


**Figure IA.7: Continued**

respect to the output price ($\partial D(\theta;T)/\partial\theta$ and $\partial E(\theta;T)/\partial\theta$, respectively). Plugging the debt and equity values and their partial derivatives into Equation (11) of our main paper, we obtain the instantaneous expected excess stock and expected excess debt returns implied by our model.

### IA.7.3. Real Options Model Comparative Statics

We finally offer comparative statics on the model-implied relations between default risk and the expected stock and debt returns in Section IV of our main paper. Toward that goal, Figure IA.7 repeats Figure 6 in that paper, this time, however, separately setting the riskfree rate $r$ (Panel A), the output price volatility $\sigma$ (Panel B), the variable production costs $c_2$ (Panel C), the fixed production costs $f$ (Panel D), the coupon payment $C$ (Panel E), and the maturity time $T$ (Panel F) to a low, the basecase (for comparison), and a high value. More specifically, we choose $r \in \{0.02, 0.04, 0.06\}$, $\sigma \in \{0.45, 0.55, 0.65\}$, $c_2 \in \{0.10, 0.30, 0.70\}$, $f \in \{0.50, 0.70, 0.90\}$, $C \in \{9.50, 10.00, 10.50\}$, and $T \in \{1.50, 2.00, 2.50\}$.

Figure IA.7 shows that the negative (or more accurately: hump-shaped) relation between default risk and the expected stock or debt return is robust to parameter value variations. Notwithstanding, Panel A shows that a higher riskfree rate flattens the default risk-expected stock return relation, while making the default risk-expected debt return relation more negative. Conversely, Panels B to D suggest that a higher volatility or variable or fixed cost boosts the value of the firm's disinvestment options, rendering the relations between default risk and the expected returns more negative. Next, Panel E reveals that while a higher coupon exerts almost no effect on the default risk-expected stock return relation, it makes the default risk-expected debt return relation more positive (negative) over low (high) default risk values. Finally, Panel F indicates that while a longer maturity time hardly affects our main conclusions, it renders the default risk-expected debt return relation more negative because a longer maturity time allows the firm to disinvest more of its assets-in-place.

## References

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2022. The distress anomaly is deeper than you think: Evidence from stocks and bonds. Review of Finance 26, 355–405.

Bai, J., Bali, T.G., Wen, Q., 2019. Common risk factors in the cross-section of corporate bond returns. Journal of Financial Economics 131, 619–642.

Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. The Journal of Finance 66, 911–946.

Bartram, S.M., Grinblatt, M., Nozawa, Y., 2025. Book-to-market, mispricing, and the cross section of corporate bond returns. Journal of Financial and Quantitative Analysis 60, 1185–1233.

Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. The Journal of Finance 63, 2899–2939.

Choi, J., 2013. What drives the value premium? The role of asset risk and leverage. The Review of Financial Studies 26, 2845–2875.

Choi, J., Richardson, M., 2016. The volatility of a firm's assets and the leverage effect. Journal of Financial Economics 121, 254–277.

Costello, A.M., 2019. The value of collateral in trade finance. Journal of Financial Economics 134, 70–90.

Dick-Nielsen, J., Feldhütter, P., Pedersen, L.H., Stolborg, C., 2025. Corporate bond factors: Replication failures and a new framework. Working paper.

Dickerson, A., Julliard, C., Mueller, P., 2025. The co-pricing factor zoo. Forthcoming in the Journal of Financial Economics.

Erens, B.B., Hoffmann, T.W., 2013. The triumph of the trade creditor in Chapter 11 reorganizations. Pratt's Journal of Bankruptcy Law 9, 3–38.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2008. Dissecting anomalies. The Journal of Finance 63, 1653–1678.

Fama, E.F., French, K.R., 2016. Dissecting anomalies with a five-factor model. The Review of Financial Studies 29, 69–103.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Fan, H., Sundaresan, S.M., 2000. Debt valuation, renegotiation, and optimal dividend policy. The Review of Financial Studies 13, 1057–1099.

Garlappi, L., Shu, T., Yan, H., 2008. Default risk, shareholder advantage, and stock returns. The Review of Financial Studies 21, 2743–2778.

Garlappi, L., Yan, H., 2011. Financial distress and the cross-section of equity returns. The Journal of Finance 66, 789–822.

Hilscher, J., Wilson, M., 2017. Credit ratings and credit risk: Is one measure enough? Management Science 63, 3414–3437.

Hooke, J.C., 2014. M&A: A Practical Guide to Doing the Deal. Wiley.

Lin, H., Wang, J., Wu, C., 2011. Liquidity risk and expected corporate bond returns. Journal of Financial Economics 99, 628–650.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Pástor, Ľ., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Scholes, M., Williams, J., 1977. Estimating betas from non-synchronous data. Journal of Financial Economics 5, 309–327.

**Table IA.1: Bond and Loan Sample Coverage**

In this table, we contrast our bond and loan samples (used in the stock-bond and stock-bond-loan-asset samples, respectively) with the CRSP-Compustat universe and also investigate credit-rating-based subsamples of those bond and loan samples. In particular, Panel A compares the entire CRSP-Compustat firm universe and the subuniverses of levered and non-levered firms (columns (1) to (3)), the entire sample of firms with bonds and the subsample of those with an asset value above $100 million (columns (4) and (5)); and the entire sample of firms with loans and the subsample of those with an asset value above $100 million (columns (6) and (7)) along their number of observations, mean and median market assets (in million $), and median book and market leverage. For the bond and loan samples, it also calculates the median proportions of firms' short plus long-term debt book values captured by either the outstanding balances of their bonds or those of their bonds and loans. Panel B considers the same statistics calculated by credit-rating-subsamples in the bond (subpanel B.1) and the loan (subpanel B.2) samples. We compute market assets as the market value of common equity plus the book value of short and long-term debt and use S&P entity credit ratings to form the subsamples in Panel B.

Panel A: Sample Coverage Relative to the CRSP-Compustat Universe

| | CRSP/Compustat Universe | | | Bond Sample | | Bond-Loan Sample | |
|---|---|---|---|---|---|---|---|
| | All | Leverage $> 0$ | Leverage $= 0$ | Leverage $> 0$ | Lev. $> 0$ & Assets $>$ \$100M | Leverage $> 0$ | Lev. $> 0$ & Assets $>$ \$100M |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Number of Observations | 1,986,230 | 1,719,398 | 266,830 | 283,871 | 283,320 | 57,494 | 57,400 |
| Average Market Assets | 4,134.5 | 4,633.4 | 919.7 | 21,222.1 | 21,263.2 | 11,862.8 | 11,882.2 |
| Median Market Assets | 238.9 | 275.0 | 113.0 | 5,283.5 | 5,302.3 | 2,608.8 | 2,614.9 |
| Median Book Leverage | 1.38 | 1.51 | 1.00 | 1.79 | 1.79 | 2.04 | 2.04 |
| Median Market Leverage | 1.24 | 1.33 | 1.00 | 1.52 | 1.52 | 1.72 | 1.72 |
| Debt% Covered by Bonds Alone | | | | 0.76 | 0.76 | 0.00 | 0.00 |
| Debt% Covered by Bonds & Loans | | | | | | 0.93 | 0.93 |

(continued on next page)

| Panel B: Sample Statistics by Entity-Rating Class | | | | | | | |
|---|---|---|---|---|---|---|---|
| | # Obs. | Mean Market Assets | Median Market Assets | Median Book Leverage | Median Market Leverage | Debt% Covered By Bonds Alone | Debt% Covered By Bonds & Loans |
| **Panel B.1: Bond Sample** | | | | | | | |
| AAA | 1,021 | 106,900.3 | 49,960.1 | 1.29 | 1.07 | 0.58 | |
| AA | 10,531 | 70,035.1 | 18,220.2 | 1.58 | 1.22 | 0.59 | |
| A | 75,960 | 39,923.3 | 12,017.8 | 1.71 | 1.36 | 0.66 | |
| BBB | 63,210 | 16,443.4 | 6,891.8 | 1.72 | 1.41 | 0.81 | |
| BB | 43,435 | 6,273.2 | 2,763.6 | 1.98 | 1.67 | 0.93 | |
| B | 24,235 | 4,271.2 | 1,533.0 | 2.28 | 2.14 | 0.99 | |
| C | 1,123 | 4,371.8 | 2,364.7 | 1.87 | 2.71 | 0.90 | |
| Unrated | 64,356 | 11,262.1 | 3,292.6 | 1.82 | 1.63 | 0.70 | |
| **Panel B.2: Loan Sample** | | | | | | | |
| AAA | 46 | 333,743.8 | 321,105.9 | 1.37 | 1.08 | 0.80 | 0.82 |
| AA | 236 | 448,775.5 | 618,719.4 | 3.80 | 2.44 | 0.39 | 0.39 |
| A | 1,685 | 109,831.8 | 20,886.6 | 1.53 | 1.22 | 0.69 | 0.81 |
| BBB | 2,218 | 36,887.7 | 11,670.1 | 1.71 | 1.34 | 0.53 | 0.96 |
| BB | 18,172 | 6,572.5 | 3,239.8 | 2.03 | 1.55 | 0.00 | 0.99 |
| B | 15,387 | 4,335.0 | 1,648.9 | 2.29 | 2.40 | 0.00 | 0.94 |
| C | 1,253 | 5,111.6 | 1,795.3 | 0.98 | 6.09 | 0.00 | 0.66 |
| Unrated | 18,497 | 5,479.3 | 2,124.3 | 2.05 | 1.68 | 0.00 | 0.90 |

## Table IA.2: Zero Price Changes and Correlations: Stock-Bond Sample

This table presents the proportions of zero-bond-price-change observations (Panel A), the first three autocorrelations of stock and bond returns (Panel B), and the cross-correlations between stock and bond returns (Panel C) in the stock-bond sample. We report all these statistics both for the whole sample and credit-rating-based subsamples based on S&P entity credit ratings. In Panel A, "single bonds" gives the proportion of zero-bond-price-change bond-month observations, while "firm bond portfolios" reports the proportion of firm-month observations for which at least one bond of a firm does not change its price. In Panel B, subpanel B.1 gives average firm-level autocorrelations, while subpanel B.2 reports portfolio-level autocorrelations, where we value-weight the portfolios using either their stock or aggregate bond capitalizations.

Panel A: Proportion of Zero-Price-Change Bond Observations

| | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
|---|---|---|---|---|---|---|---|---|---|
| Observations | 1,712,230 | 6,262 | 108,496 | 677,645 | 433,379 | 136,057 | 58,604 | 3,264 | 288,523 |
| Single Bonds | 1.70% | 0.03% | 0.63% | 1.02% | 1.09% | 4.86% | 5.86% | 4.81% | 2.28% |
| Firm Bond Portfolios | 6.24% | 0.20% | 4.63% | 4.02% | 3.63% | 10.72% | 10.83% | 10.27% | 7.13% |

Panel B: Stock and Bond Autocorrelations

Panel B.1: Firm-Level Autocorrelation

| | Lag | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
|---|---|---|---|---|---|---|---|---|---|---|
| Stock | 1 | –0.01 | –0.02 | –0.03 | –0.03 | –0.02 | –0.02 | 0.01 | 0.05 | –0.01 |
| | 2 | –0.01 | –0.04 | –0.04 | –0.05 | –0.04 | –0.02 | –0.01 | –0.12 | –0.01 |
| | 3 | –0.01 | –0.05 | –0.03 | –0.02 | –0.02 | –0.01 | 0.00 | –0.08 | –0.01 |
| Bond | 1 | –0.02 | 0.14 | 0.07 | 0.01 | –0.03 | –0.06 | –0.03 | 0.17 | 0.00 |
| | 2 | –0.03 | –0.08 | –0.04 | –0.04 | –0.02 | –0.03 | –0.01 | 0.09 | –0.04 |
| | 3 | –0.02 | –0.02 | –0.04 | –0.02 | 0.00 | –0.02 | 0.00 | 0.02 | –0.03 |

Panel B.2: Portfolio-Level Autocorrelation

| | Lag | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
|---|---|---|---|---|---|---|---|---|---|---|
| Stock | 1 | 0.05 | –0.05 | –0.04 | 0.03 | 0.07 | 0.10 | 0.12 | 0.15 | 0.08 |
| | 2 | –0.06 | –0.04 | –0.08 | –0.07 | –0.06 | –0.04 | –0.05 | 0.10 | –0.06 |
| | 3 | 0.00 | –0.01 | 0.03 | 0.01 | 0.02 | 0.00 | 0.09 | 0.07 | –0.03 |
| Bond | 1 | 0.10 | 0.12 | 0.12 | 0.10 | 0.10 | 0.08 | 0.08 | 0.12 | 0.09 |
| | 2 | –0.09 | –0.10 | –0.04 | –0.10 | –0.08 | –0.10 | –0.06 | 0.04 | –0.10 |
| | 3 | –0.07 | –0.05 | –0.09 | –0.08 | –0.04 | –0.02 | 0.01 | 0.01 | –0.04 |

Panel C: Cross-Correlations with Bond Returns

| | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
|---|---|---|---|---|---|---|---|---|---|
| Bond, Equity | 0.26 | 0.14 | 0.14 | 0.16 | 0.20 | 0.32 | 0.37 | 0.52 | 0.21 |
| Bond, Equity(–1) | 0.06 | –0.02 | –0.03 | 0.00 | 0.05 | 0.07 | 0.10 | 0.14 | 0.06 |
| Bond, Equity(–2) | 0.00 | 0.04 | –0.02 | –0.03 | –0.01 | 0.00 | 0.01 | 0.02 | 0.00 |
| Bond, Equity(–3) | 0.00 | –0.01 | –0.02 | –0.02 | 0.00 | 0.00 | 0.01 | 0.02 | –0.01 |
| Equity, Bond(–1) | 0.04 | 0.02 | 0.04 | 0.02 | 0.01 | 0.05 | 0.07 | 0.04 | 0.04 |
| Equity, Bond(–2) | 0.00 | 0.01 | 0.04 | 0.00 | –0.02 | 0.01 | 0.02 | 0.05 | 0.01 |
| Equity, Bond(–3) | 0.01 | 0.02 | 0.01 | 0.01 | 0.02 | 0.03 | 0.02 | –0.02 | 0.00 |

## Table IA.3: Zero Price Changes and Correlations: Stock-Bond-Loan-Asset Sample

This table presents the proportions of zero-loan-price-change observations (Panel A), the first three autocorrelations of stock, bond, and loan returns (Panel B), and the cross-correlations between stock and either bond or loan returns (Panel C) in the stock-bond-loan-asset sample. We report all these statistics both for the whole sample and credit-rating-based subsamples based on S&P entity credit ratings. In Panel A, "single loans" gives the proportion of zero-loan-price-change loan-month observations, while "firm loan portfolios" reports the proportion of firm-month observations for which at least one loan of a firm does not change its price. We report the single-loan statistics separately for our quotes, transaction prices, and quotes conditional on at least one trade. In Panel B, subpanel B.1 gives average firm-level autocorrelations, while subpanel B.2 reports portfolio-level autocorrelations, where we value-weight the portfolios using either their stock or aggregate bond or loan capitalizations. In Panel C, we report the correlations with bond returns in Panel C.1 and those with loan returns in Panel C.2.

| | Panel A: Proportion of Zero-Price-Change Loan Observations | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
| Observations | 234,240 | 46 | 416 | 3,974 | 30,041 | 34,116 | 4,620 | 3,268 | 157,759 |
| Single Loans | 33.91% | 43.48% | 44.95% | 39.31% | 26.72% | 34.60% | 47.79% | 24.76% | 34.74% |
| Quotes | 34.19% | 52.17% | 45.43% | 39.63% | 47.88% | 34.82% | 27.02% | 25.15% | 35.03% |
| Transaction Prices | 1.03% | 2.17% | 0.72% | 1.36% | 0.80% | 1.16% | 1.07% | 0.73% | 0.99% |
| Quotes \| Trading | 0.24% | 6.52% | 0.24% | 0.33% | 0.11% | 0.21% | 0.29% | 0.40% | 0.24% |
| Firm Loan Portfolios | 42.99% | 43.48% | 50.00% | 50.38% | 56.73% | 43.84% | 35.54% | 32.65% | 43.77% |

Panel B: Stock, Bond, and Loan Autocorrelations

| | Panel B.1: Firm-Level Autocorrelation | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lag | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
| Stock | 1 | –0.01 | –0.07 | –0.11 | 0.03 | –0.05 | –0.05 | 0.00 | –0.14 | –0.02 |
| | 2 | –0.02 | –0.02 | 0.05 | –0.11 | –0.03 | –0.02 | –0.01 | –0.10 | –0.03 |
| | 3 | –0.01 | 0.13 | –0.18 | –0.03 | –0.03 | –0.01 | –0.01 | 0.02 | –0.01 |
| Bond | 1 | –0.04 | 0.02 | 0.06 | 0.07 | –0.06 | –0.11 | 0.00 | 0.16 | –0.07 |
| | 2 | –0.01 | 0.20 | –0.02 | –0.09 | –0.04 | –0.04 | 0.00 | 0.05 | –0.01 |
| | 3 | 0.02 | 0.13 | 0.09 | –0.01 | 0.02 | 0.02 | 0.02 | 0.04 | 0.00 |
| Loan | 1 | 0.06 | 0.02 | –0.07 | 0.12 | 0.08 | 0.05 | 0.06 | 0.10 | 0.05 |
| | 2 | 0.00 | –0.06 | –0.03 | 0.02 | 0.08 | –0.03 | –0.02 | –0.09 | 0.00 |
| | 3 | –0.01 | 0.06 | 0.08 | –0.01 | 0.13 | –0.01 | –0.01 | 0.05 | –0.01 |

| | Panel B.2: Portfolio-Level Autocorrelation | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lag | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
| Stock | 1 | 0.09 | –0.07 | –0.12 | 0.04 | 0.00 | 0.04 | 0.12 | 0.08 | 0.09 |
| | 2 | –0.04 | –0.02 | –0.06 | –0.10 | –0.12 | –0.07 | –0.09 | 0.12 | –0.04 |
| | 3 | 0.10 | 0.13 | –0.15 | 0.10 | 0.10 | 0.02 | 0.14 | 0.06 | 0.06 |
| Bond | 1 | 0.02 | 0.03 | 0.09 | 0.09 | 0.05 | –0.03 | –0.03 | 0.04 | 0.03 |
| | 2 | –0.13 | 0.20 | 0.04 | –0.18 | –0.10 | –0.16 | –0.04 | 0.05 | 0.04 |
| | 3 | –0.03 | 0.13 | 0.18 | –0.16 | 0.03 | 0.03 | 0.05 | –0.02 | 0.00 |
| Loan | 1 | 0.43 | 0.02 | 0.24 | 0.30 | 0.24 | 0.35 | 0.47 | 0.32 | 0.31 |
| | 2 | 0.14 | –0.06 | –0.13 | 0.15 | 0.13 | 0.06 | 0.22 | 0.05 | 0.06 |
| | 3 | 0.05 | 0.06 | –0.23 | 0.02 | 0.05 | –0.06 | 0.09 | 0.10 | –0.01 |

(continued on next page)

| Panel C: Cross-Correlations with Bond and Loan Returns | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Panel C.1: Cross-Correlations with Bond Returns | | | | | | | | | |
| | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
| Bond, Equity | 0.30 | 0.26 | 0.08 | 0.09 | 0.21 | 0.31 | 0.32 | 0.45 | 0.24 |
| Bond, Equity(–1) | 0.08 | 0.13 | 0.02 | 0.05 | 0.02 | 0.02 | 0.09 | 0.13 | 0.06 |
| Bond, Equity(–2) | 0.00 | 0.24 | –0.06 | –0.02 | –0.01 | –0.01 | –0.01 | 0.06 | –0.02 |
| Bond, Equity(–3) | 0.01 | 0.20 | 0.21 | 0.02 | –0.03 | 0.01 | 0.03 | 0.00 | 0.00 |
| Equity, Bond(–1) | 0.04 | 0.09 | 0.06 | 0.01 | 0.02 | 0.00 | 0.06 | 0.07 | 0.02 |
| Equity, Bond(–2) | 0.00 | 0.04 | 0.16 | –0.04 | –0.06 | –0.03 | –0.01 | 0.04 | –0.01 |
| Equity, Bond(–3) | 0.02 | –0.09 | –0.02 | 0.03 | 0.00 | 0.04 | 0.04 | 0.01 | –0.01 |
| Panel C.2: Cross-Correlations with Loan Returns | | | | | | | | | |
| | ALL | AAA | AA | A | BBB | BB | B | ~C | UNRATED |
| Loan, Equity | 0.22 | 0.05 | 0.18 | 0.14 | 0.20 | 0.23 | 0.25 | 0.24 | 0.21 |
| Loan, Equity(–1) | 0.15 | –0.19 | 0.21 | 0.16 | 0.07 | 0.11 | 0.15 | 0.22 | 0.13 |
| Loan, Equity(–2) | 0.07 | 0.29 | 0.05 | 0.02 | 0.12 | 0.05 | 0.06 | 0.10 | 0.06 |
| Loan, Equity(–3) | 0.02 | –0.25 | 0.05 | –0.05 | 0.01 | 0.00 | 0.02 | 0.00 | 0.03 |
| Equity, Loan(–1) | 0.02 | 0.11 | –0.15 | 0.07 | 0.03 | –0.01 | 0.03 | –0.08 | 0.03 |
| Equity, Loan(–2) | 0.02 | –0.15 | –0.06 | 0.08 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 |
| Equity, Loan(–3) | 0.03 | 0.16 | 0.18 | 0.02 | 0.00 | 0.05 | 0.02 | 0.04 | 0.02 |

## Table IA.4: Stock and Bond Portfolio Characteristics

The table offers the mean characteristics of stock and bond portfolios univariately sorted on distress risk in the stock-bond sample. Panels A and B focus on the stock and firm-specific bond portfolios, respectively. We first form an equally-weighted average of each characteristic first by portfolio and sample month and then average over our sample period. The stock characteristics include the market beta, market capitalization (size; in billion $), the book-to-market ratio, the intermediate-term past (momentum) return, asset growth, and profitability. The bond characteristics include the bond market beta, the value-weighted average and aggregate bond capitalization (size; in billion $), years-to-maturity, the credit rating, the coupon rate, downside risk, reversal, the liquidity beta, and illiquidity. See Table A1 in Appendix A at the end of the main paper for details about the characteristics also used in the main paper. The coupon rate is a bond's coupon-to-price ratio, its liquidity beta its loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see Lin et al. (2011)), and its illiquidity its daily-price-change autocovariance (see Bao et al. (2011)).

| | Distress Risk Decile Portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 (Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High) |
| Panel A: Stock Portfolio Characteristics | | | | | | | | | | |
| Market Beta | 0.82 | 0.81 | 0.79 | 0.77 | 0.76 | 0.75 | 0.74 | 0.75 | 0.78 | 0.88 |
| Market Size | 3.88 | 5.34 | 5.75 | 5.58 | 4.90 | 4.30 | 3.49 | 2.56 | 1.80 | 1.02 |
| Book-to-Market | 0.57 | 0.54 | 0.56 | 0.58 | 0.61 | 0.64 | 0.67 | 0.69 | 0.69 | 0.67 |
| Momentum | 0.07 | 0.10 | 0.10 | 0.10 | 0.09 | 0.09 | 0.09 | 0.08 | 0.07 | 0.03 |
| Asset Growth | 0.17 | 0.16 | 0.14 | 0.14 | 0.13 | 0.13 | 0.13 | 0.14 | 0.15 | 0.18 |
| Profitability | 0.38 | 0.37 | 0.35 | 0.33 | 0.30 | 0.28 | 0.25 | 0.23 | 0.23 | 0.23 |
| Panel B: Bond Portfolio Characteristics | | | | | | | | | | |
| Bond Market Beta | 0.42 | 0.45 | 0.46 | 0.47 | 0.47 | 0.47 | 0.46 | 0.45 | 0.44 | 0.43 |
| Market Size | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.37 | 0.36 | 0.36 | 0.34 |
| Total Market Size | 1.79 | 2.02 | 2.25 | 2.36 | 2.43 | 2.48 | 2.7 | 2.52 | 2.19 | 1.53 |
| Maturity | 9.51 | 10.00 | 10.20 | 10.21 | 10.11 | 10.01 | 9.66 | 9.24 | 8.75 | 8.04 |
| Credit Rating | 7.93 | 7.59 | 7.53 | 7.56 | 7.67 | 7.78 | 7.97 | 8.20 | 8.71 | 10.02 |
| Coupon | 7.51 | 7.32 | 7.29 | 7.32 | 7.36 | 7.41 | 7.51 | 7.62 | 7.84 | 8.47 |
| Downside Risk | 1.64 | 1.63 | 1.57 | 1.62 | 1.63 | 1.64 | 1.67 | 1.74 | 1.84 | 2.40 |
| Reversal | 0.90 | 0.89 | 0.84 | 0.83 | 0.82 | 0.79 | 0.77 | 0.75 | 0.71 | 0.40 |
| Liquidity Beta | 0.03 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.04 | 0.04 | 0.07 |
| Illiquidity | 0.25 | 0.20 | 0.20 | 0.25 | 0.26 | 0.24 | 0.32 | 0.32 | 0.31 | 0.53 |

# Table IA.5: Stock and Bond Long Horizon Distress Premiums

The table offers the risk-adjusted stock (Panel A) and bond (Panel B) mean returns of the value or equally-weighted or the Fama and MacBeth (1973) regression high-minus-low distress decile spread portfolio separately for each month over the year after the portfolio formation date in the stock-bond sample. To create the first two spread portfolios, we sort our sample stocks or firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We then value or equally weight the portfolios and hold them over each month from $t$ to $t+11$, where we use a firm's total stock or bond capitalization to construct the value-weights. We finally form the spread portfolios as long the top distress decile portfolio and short the bottom and compute their FF6S (stocks) or SB14 (bonds) alphas. Conversely, we construct the Fama and MacBeth (1973) risk-adjusted spread portfolio return from a regression of the stock or bond return over each month from $t$ to $t+11$ on nine distress decile portfolio dummy variables omitting the dummy for the first decile and controls, choosing the coefficient of the decile-10 dummy as the risk-adjusted spread portfolio return. In Panel B, we use both standard (Ret=S) and Bartram, Grinblatt and Nozawa (2025; Ret=BGN) returns to create the spread portfolio returns. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length.

| | | Month After Portfolio Formation | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: Stocks | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | −0.98 | −1.05 | −1.01 | −0.60 | −0.64 | −1.05 | −0.61 | −0.49 | −0.47 | −0.46 | −0.94 | −0.03 |
| | | [−2.25] | [−3.55] | [−3.34] | [−2.32] | [−2.51] | [−3.70] | [−2.26] | [−1.66] | [−2.25] | [−1.72] | [−3.31] | [−0.08] |
| Equally-Weighted Sorts | S | −0.84 | −1.08 | −1.22 | −0.95 | −0.81 | −0.97 | −0.67 | −0.46 | −0.63 | −0.48 | −0.61 | −0.35 |
| | | [−3.73] | [−4.39] | [−5.81] | [−5.60] | [−4.59] | [−5.40] | [−4.09] | [−2.63] | [−4.46] | [−3.04] | [−3.60] | [−2.01] |
| FM Regressions | S | −0.55 | −1.07 | −1.04 | −0.64 | −0.70 | −0.67 | −0.48 | −0.25 | −0.42 | −0.23 | −0.32 | −0.21 |
| | | [−2.27] | [−4.98] | [−5.82] | [−3.93] | [−4.95] | [−4.76] | [−3.56] | [−1.76] | [−3.35] | [−1.71] | [−2.20] | [−1.61] |
| Panel B: Bonds | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | −0.47 | −0.27 | −0.29 | −0.20 | −0.15 | −0.19 | −0.15 | −0.06 | −0.13 | −0.12 | −0.19 | −0.14 |
| | | [−7.51] | [−4.53] | [−6.24] | [−4.03] | [−1.77] | [−3.47] | [−2.92] | [−0.96] | [−2.70] | [−2.25] | [−2.79] | [−2.38] |
| Equally-Weighted Sorts | S | −0.41 | −0.23 | −0.22 | −0.16 | −0.17 | −0.14 | −0.12 | −0.05 | −0.10 | −0.13 | −0.18 | −0.13 |
| | | [−7.27] | [−4.72] | [−5.81] | [−3.21] | [−2.34] | [−2.54] | [−2.75] | [−0.96] | [−2.25] | [−2.36] | [−3.06] | [−2.66] |
| FM Regressions | S | −0.39 | −0.13 | −0.07 | −0.05 | −0.06 | −0.02 | −0.02 | 0.02 | −0.03 | −0.02 | −0.04 | −0.04 |
| | | [−6.04] | [−3.19] | [−1.92] | [−1.19] | [−1.86] | [−0.63] | [−0.51] | [0.48] | [−0.80] | [−0.53] | [−1.04] | [−1.13] |
| Value-Weighted Sorts | BGN | −0.47 | −0.26 | −0.30 | −0.21 | −0.11 | −0.19 | −0.15 | −0.21 | 0.01 | −0.09 | −0.19 | −0.12 |
| | | [−7.59] | [−4.24] | [−6.52] | [−4.01] | [−1.20] | [−3.52] | [−2.96] | [−1.39] | [0.10] | [−1.62] | [−2.72] | [−1.99] |
| Equally-Weighted Sorts | BGN | −0.41 | −0.23 | −0.21 | −0.16 | −0.18 | −0.14 | −0.11 | −0.05 | −0.09 | −0.13 | −0.17 | −0.13 |
| | | [−7.23] | [−4.63] | [−5.75] | [−3.33] | [−2.40] | [−2.56] | [−2.75] | [−1.07] | [−2.06] | [−2.45] | [−2.97] | [−2.60] |
| FM Regressions | BGN | −0.38 | −0.12 | −0.06 | −0.04 | −0.06 | −0.01 | 0.00 | 0.02 | 0.00 | −0.02 | −0.02 | −0.03 |
| | | [−5.98] | [−3.04] | [−1.46] | [−1.00] | [−1.57] | [−0.38] | [−0.04] | [0.72] | [−0.11] | [−0.53] | [−0.48] | [−0.86] |

### Table IA.6: Bond Portfolios Double-Sorted on Distress and Credit Ratings

The table presents the SB14 alphas of single-bond portfolios double-sorted on corporate distress risk and bond credit ratings. In Panel A, we first sort our sample bonds into portfolios according to whether a bond's most recent rating at the end of month $t-1$ is high investment grade (rating value: 1 to 4), low investment grade (5 to 10), or speculative (above 10). Within each rating portfolio, we next sort them into portfolios according to the tercile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. In Panel B, we reverse the order, first sorting into distress and then credit rating portfolios. We value-weight the portfolios and hold them over month $t$, using a bond's market capitalization as weight. Within each rating (distress) portfolio, we form a portfolio long the top distress (lowest rating) portfolio and short the bottom (highest rating) portfolio. The table reports the mean number of assets and the alpha of the SB14 stock-bond factor model. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length.

Panel A: Dependent Sort on Credit Rating and Distress Risk

| | High IG | | Low IG | | Speculative | |
|---|---|---|---|---|---|---|
| Distress Risk | Obs | Alpha | Obs | Alpha | Obs | Alpha |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 1 (Low Distress) | 399 | 0.13 | 609 | 0.18 | 204 | 0.34 |
| 2 | 405 | 0.09 | 616 | 0.06 | 206 | 0.14 |
| 3 (High Distress) | 425 | 0.06 | 622 | 0.06 | 210 | –0.10 |
| High–Low | | –0.07 | | –0.11 | | –0.44 |
| $t$–statistic | | [–2.08] | | [–3.62] | | [–6.84] |

Panel B: Dependent Sort on Distress Risk and Credit Rating

| | Distress Tercile 1 | | Distress Tercile 2 | | Distress Tercile 3 | |
|---|---|---|---|---|---|---|
| Credit Rating | Obs | Alpha | Obs | Alpha | Obs | Alpha |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| High IG | 439 | 0.13 | 447 | 0.15 | 344 | 0.04 |
| Low IG | 609 | 0.18 | 652 | 0.06 | 587 | 0.01 |
| Speculative | 165 | 0.34 | 156 | 0.18 | 300 | –0.03 |
| Speculative–High | | 0.21 | | 0.03 | | –0.07 |
| $t$–statistic | | [4.65] | | [0.34] | | [–1.30] |

## Table IA.7: Stock, Bond, Loan, and Firm-Asset Portfolio Characteristics

The table offers the mean characteristics of stock, bond, loan, and firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample. Panels A to D focus on the stock, firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios, respectively. We first form an equally-weighted average of each characteristic first by portfolio and sample month and then average over our sample period. The stock characteristics include the market beta, market capitalization (size; in billion), the book-to-market ratio, the intermediate-term past (momentum) return, asset growth, and profitability. The bond characteristics include the bond market beta, the value-weighted average and aggregate bond capitalization (size; in billion $), years-to-maturity, the credit rating, the coupon rate, downside risk, reversal, the liquidity beta, and illiquidity. The loan characteristics include the value-weighted average and aggregate loan capitalization (size; in billion $) and years-to-maturity. The firm-asset characteristics include the total firm-asset capitalization. See Table A1 in Appendix A at the end of the main paper for details about the characteristics also used in the main paper. The coupon rate is a bond's coupon-to-price ratio, its liquidity beta its loading on the orthogonalized aggregate signed volume coefficient from first-stage regressions (see Lin et al. (2011)), and its illiquidity its daily-price-change autocovariance (see Bao et al. (2011)).

| | Distress Risk Quintile Portfolios | | | | |
|---|---|---|---|---|---|
| | 1 (Low) | 2 | 3 | 4 | 5 (High) |
| **Panel A: Stock Portfolio Characteristics** | | | | | |
| Market Beta | 0.77 | 0.82 | 0.89 | 1.01 | 1.27 |
| Market Size | 3.47 | 3.11 | 2.52 | 1.78 | 0.75 |
| Book-to-Market | 0.45 | 0.48 | 0.52 | 0.60 | 0.72 |
| Momentum | 0.08 | 0.06 | 0.03 | –0.03 | –0.23 |
| Asset Growth | 0.14 | 0.13 | 0.13 | 0.13 | 0.11 |
| Profitability | 0.30 | 0.27 | 0.26 | 0.26 | 0.25 |
| **Panel B: Bond Portfolio Characteristics** | | | | | |
| Bond Market Beta | 0.27 | 0.28 | 0.32 | 0.33 | 0.42 |
| Market Size | 0.55 | 0.55 | 0.55 | 0.54 | 0.44 |
| Total Market Size | 3.00 | 3.79 | 3.95 | 3.72 | 1.94 |
| Maturity | 7.31 | 7.08 | 6.81 | 6.54 | 6.35 |
| Credit Rating | 11.70 | 12.25 | 12.78 | 13.41 | 14.75 |
| Coupon | 7.26 | 7.41 | 7.66 | 7.93 | 8.40 |
| Downside Risk | 1.60 | 1.76 | 2.01 | 2.36 | 3.59 |
| Reversal | 1.02 | 1.03 | 0.99 | 0.76 | –0.49 |
| Liquidity Beta | 0.07 | 0.08 | 0.11 | 0.12 | 0.18 |
| Illiquidity | 0.36 | 0.49 | 0.57 | 0.87 | 1.69 |
| **Panel C: Loan Portfolio Characteristics** | | | | | |
| Market Size | 0.43 | 0.46 | 0.49 | 0.49 | 0.43 |
| Total Market Size | 0.52 | 0.58 | 0.61 | 0.63 | 0.54 |
| Maturity | 4.11 | 4.10 | 4.12 | 4.12 | 4.01 |
| **Panel D: Asset Portfolio Characteristics** | | | | | |
| Market Size | 5.28 | 5.01 | 4.51 | 3.74 | 2.35 |

## Table IA.8: Stock, Bond, Loan, and Firm-Asset Long Horizon Distress Premiums

The table offers the risk-adjusted stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) mean returns of the value or equally-weighted or the Fama and MacBeth (1973) regression high-minus-low distress quintile spread portfolio separately for each month over the year after the portfolio formation date in the stock-bond-loan-asset sample. To create the first two spread portfolios, we sort our sample stocks, firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), firm-specific loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), and firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We then value or equally weight the portfolios and hold them over each month from $t$ to $t+11$, where we use a firm's total stock, bond, loan, and firm-asset capitalization to construct the value-weights. We finally form the spread portfolios as long the top distress quintile portfolio and short the bottom and compute their FF6S (stocks), SB14 (bonds), SB14 (loans), and SB17 (firm assets) alphas. Conversely, we construct the Fama and MacBeth (1973) risk-adjusted spread portfolio return from a regression of the stock, bond, loan, or firm-asset return over each month from $t$ to $t+11$ on four distress quintile portfolio dummy variables omitting the dummy for the first quintile and controls, choosing the coefficient of the quintile-5 dummy as the risk-adjusted spread portfolio return. In Panels B, C, and D, we use both standard (Ret=S) and Bartram, Grinblatt and Nozawa (2025; Ret=BGN) returns to create the spread portfolio returns. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length.

| | | Month After Portfolio Formation | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Panel A: Stocks | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | −1.12 | −0.92 | −0.78 | −0.13 | −0.38 | 0.18 | −0.05 | −0.30 | 0.08 | −0.33 | 0.14 | 0.54 |
| | | [−2.49] | [−2.54] | [−1.96] | [−0.31] | [−1.39] | [0.69] | [−0.15] | [−0.78] | [0.21] | [−1.10] | [0.50] | [1.85] |
| Equally-Weighted Sorts | S | −0.79 | −0.65 | −0.32 | −0.17 | −0.18 | 0.33 | 0.05 | −0.16 | 0.11 | 0.02 | 0.04 | 0.56 |
| | | [−2.20] | [−1.89] | [−0.95] | [−0.44] | [−0.77] | [1.20] | [0.17] | [−0.58] | [0.44] | [0.07] | [0.18] | [2.87] |
| FM Regressions | S | −0.42 | −0.79 | −0.23 | 0.19 | 0.17 | 0.09 | 0.30 | 0.06 | −0.11 | −0.07 | 0.20 | 0.54 |
| | | [−1.00] | [−2.12] | [−0.72] | [0.81] | [0.68] | [0.47] | [1.31] | [0.28] | [−0.55] | [−0.34] | [1.05] | [2.68] |
| Panel B: Bonds | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | −0.87 | −0.44 | −0.45 | −0.22 | −0.15 | −0.38 | −0.08 | −0.13 | −0.16 | −0.04 | 0.00 | 0.03 |
| | | [−3.52] | [−2.27] | [−3.06] | [−1.47] | [−0.74] | [−2.73] | [−0.49] | [−0.79] | [−1.17] | [−0.22] | [0.03] | [0.20] |
| Equally-Weighted Sorts | S | −0.79 | −0.22 | −0.17 | −0.22 | −0.07 | −0.19 | −0.04 | −0.12 | −0.10 | −0.04 | −0.05 | 0.06 |
| | | [−3.61] | [−1.21] | [−1.08] | [−1.57] | [−0.37] | [−1.29] | [−0.31] | [−0.91] | [−0.81] | [−0.32] | [−0.43] | [0.62] |
| FM Regressions | S | −0.73 | −0.15 | −0.15 | −0.14 | 0.00 | 0.03 | −0.08 | −0.03 | 0.00 | 0.02 | −0.02 | 0.09 |
| | | [−3.38] | [−1.31] | [−1.27] | [−1.01] | [0.01] | [0.26] | [−0.94] | [−0.43] | [0.01] | [0.29] | [−0.18] | [1.24] |
| Value-Weighted Sorts | BGN | −0.95 | −0.44 | −0.46 | −0.37 | −0.26 | −0.66 | −0.23 | −0.14 | −0.31 | −0.19 | −0.15 | −0.07 |
| | | [−3.73] | [−2.76] | [−3.02] | [−2.26] | [−1.01] | [−2.43] | [−1.29] | [−0.80] | [−1.41] | [−0.86] | [−0.89] | [−0.37] |

(continued on next page)

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel B: Bonds (continued)** | | | | | | | | | | | | | |
| Equally-Weighted Sorts | BGN | –0.85 | –0.32 | –0.23 | –0.27 | –0.27 | –0.46 | –0.19 | –0.08 | –0.22 | –0.17 | –0.13 | –0.01 |
| | | [–3.78] | [–2.12] | [–1.59] | [–2.14] | [–1.31] | [–1.93] | [–1.10] | [–0.65] | [–1.15] | [–0.83] | [–0.86] | [–0.06] |
| FM Regressions | BGN | –0.99 | 0.00 | –0.78 | –0.10 | –0.12 | 0.22 | 0.06 | –0.02 | –0.01 | –0.10 | –0.12 | 0.26 |
| | | [–2.86] | [–0.00] | [–1.09] | [–0.75] | [–0.91] | [1.26] | [0.60] | [–0.26] | [–0.05] | [–0.87] | [–0.93] | [1.40] |
| **Panel C: Loans** | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | –0.36 | –0.27 | –0.29 | –0.21 | –0.14 | –0.16 | –0.10 | –0.02 | 0.00 | –0.03 | 0.02 | 0.01 |
| | | [–2.89] | [–2.40] | [–2.97] | [–2.04] | [–1.20] | [–1.33] | [–1.03] | [–0.21] | [–0.04] | [–0.30] | [0.16] | [0.09] |
| Equally-Weighted Sorts | S | –0.35 | –0.22 | –0.26 | –0.21 | –0.15 | –0.07 | –0.04 | –0.06 | –0.04 | –0.02 | –0.03 | 0.03 |
| | | [–2.99] | [–2.36] | [–2.99] | [–2.37] | [–1.55] | [–0.69] | [–0.53] | [–0.79] | [–0.60] | [–0.24] | [–0.29] | [0.49] |
| FM Regressions | S | –0.28 | –0.19 | –0.15 | –0.08 | –0.03 | –0.03 | –0.01 | –0.02 | 0.03 | 0.02 | –0.03 | 0.08 |
| | | [–2.28] | [–2.27] | [–2.25] | [–1.09] | [–0.42] | [–0.57] | [–0.23] | [–0.34] | [0.89] | [0.29] | [–0.52] | [1.37] |
| Value-Weighted Sorts | BGN | –0.32 | –0.23 | –0.33 | –0.17 | –0.16 | –0.25 | –0.11 | 0.01 | –0.03 | –0.05 | –0.05 | –0.02 |
| | | [–3.21] | [–2.55] | [–4.23] | [–1.86] | [–1.83] | [–2.83] | [–1.43] | [0.11] | [–0.42] | [–0.55] | [–0.38] | [–0.34] |
| Equally-Weighted Sorts | BGN | –0.29 | –0.18 | –0.26 | –0.14 | –0.15 | –0.12 | –0.06 | –0.03 | –0.04 | –0.02 | –0.06 | 0.01 |
| | | [–2.98] | [–2.43] | [–3.44] | [–1.76] | [–1.88] | [–1.40] | [–0.72] | [–0.34] | [–0.64] | [–0.28] | [–0.60] | [0.17] |
| FM Regressions | BGN | –0.22 | –0.12 | –0.13 | –0.02 | –0.02 | –0.03 | 0.01 | 0.00 | 0.05 | 0.02 | –0.05 | 0.10 |
| | | [–2.18] | [–2.03] | [–2.25] | [–0.29] | [–0.41] | [–0.66] | [0.22] | [–0.04] | [1.43] | [0.44] | [–0.71] | [1.94] |
| **Panel D: Firm Assets** | | | | | | | | | | | | | |
| Value-Weighted Sorts | S | –0.80 | –0.67 | –0.30 | –0.09 | –0.22 | –0.12 | 0.01 | –0.24 | –0.33 | –0.08 | 0.01 | 0.36 |
| | | [–2.64] | [–2.79] | [–1.28] | [–0.38] | [–1.17] | [–0.65] | [0.06] | [–1.17] | [–1.51] | [–0.48] | [0.04] | [2.28] |
| Equally-Weighted Sorts | S | –0.58 | –0.72 | –0.05 | –0.06 | –0.06 | –0.01 | 0.05 | –0.19 | –0.27 | 0.05 | –0.02 | 0.39 |
| | | [–3.02] | [–3.13] | [–0.30] | [–0.29] | [–0.22] | [–0.06] | [0.25] | [–1.14] | [–1.81] | [0.42] | [–0.14] | [3.63] |
| FM Regressions | S | –0.54 | –0.54 | –0.44 | –0.11 | –0.21 | –0.21 | –0.01 | –0.12 | –0.21 | –0.08 | –0.18 | 0.25 |
| | | [–2.52] | [–2.90] | [–2.53] | [–0.85] | [–1.39] | [–1.93] | [–0.04] | [–0.85] | [–1.76] | [–0.83] | [–1.31] | [2.12] |
| Value-Weighted Sorts | BGN | –0.59 | –0.41 | –0.36 | –0.06 | –0.28 | –0.29 | 0.00 | –0.21 | –0.19 | 0.10 | –0.05 | 0.26 |
| | | [–2.20] | [–1.83] | [–1.53] | [–0.27] | [–1.51] | [–1.37] | [0.01] | [–1.30] | [–1.07] | [0.60] | [–0.35] | [1.72] |
| Equally-Weighted Sorts | BGN | –0.36 | –0.53 | –0.09 | 0.03 | –0.14 | –0.22 | 0.02 | –0.18 | –0.21 | 0.16 | –0.04 | 0.32 |
| | | [–2.21] | [–2.79] | [–0.53] | [0.17] | [–0.63] | [–0.92] | [0.12] | [–1.37] | [–1.48] | [1.20] | [–0.38] | [2.50] |
| FM Regressions | BGN | –0.42 | –0.37 | –0.45 | –0.04 | –0.29 | –0.25 | 0.06 | –0.07 | –0.10 | –0.08 | –0.21 | 0.24 |
| | | [–2.41] | [–1.88] | [–2.76] | [–0.29] | [–2.06] | [–2.81] | [0.50] | [–0.52] | [–0.75] | [–0.85] | [–1.70] | [2.37] |

## Table IA.9: Bond Distress Portfolios: Transaction-Price Subsample

The table offers the SB14 and SB15 alphas of bond portfolios univariately sorted on distress risk in the stock-bond sample exclusively using TRACE transaction prices to calculate bond returns. Panels A and B focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month $t$, where we use a firm's total bond capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the fifth (top) [top] decile portfolio and short the bottom (fifth) [bottom] ("Middle–Low" ("High–Middle") ["High–Low"]). SB14 and SB15 indicate the 14-factor stock-bond model and the same model plus a liquidity factor based on Bao et al.'s (2011) bond illiquidity proxy, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

| | Value-Weighted Portfolios | | Equally-Weighted Portfolios | |
|---|---|---|---|---|
| | Monthly Alpha | Monthly Alpha (incl. Liquidity Control) | Monthly Alpha | Monthly Alpha (incl. Liquidity Control) |
| | (1) | (2) | (3) | (4) |
| Panel A: Month-End to Month-End Bond Returns (Mean Monthly # Per Porfolio: 70) | | | | |
| Middle–Low | –0.09 | –0.09 | –0.06 | –0.06 |
| | [–2.29] | [–2.36] | [–2.11] | [–2.28] |
| High–Middle | –0.44 | –0.43 | –0.50 | –0.49 |
| | [–4.61] | [–4.34] | [–4.97] | [–4.82] |
| High–Low | –0.53 | –0.52 | –0.56 | –0.55 |
| | [–5.80] | [–5.69] | [–6.04] | [–5.77] |
| Alpha Factors | SB14 | SB15 | SB14 | SB15 |
| Panel B: Bartram, Grinblatt and Nozawa (2025) Bond Returns (Mean Monthly # Per Porfolio: 83) | | | | |
| Middle–Low | –0.08 | –0.08 | –0.07 | –0.07 |
| | [–2.61] | [–2.62] | [–3.03] | [–3.00] |
| High–Middle | –0.41 | –0.40 | –0.42 | –0.41 |
| | [–4.67] | [–4.31] | [–4.77] | [–4.53] |
| High–Low | –0.49 | –0.48 | –0.49 | –0.48 |
| | [–5.66] | [–5.43] | [–5.27] | [–5.03] |
| Alpha Factors | SB14 | SB15 | SB14 | SB15 |

### Table IA.10: Bond Regressions on Distress Risk: Transaction-Price Subsample

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of all, investment-grade (IG), and speculative-grade (SG) firm-specific bond portfolios over month $t$ on two distress dummy variables and controls at the end of month $t-1$ in the stock-bond sample exclusively using TRACE transaction prices to calculate bond returns and controlling for illiquidity and liquidity risk in columns (2), (4), (6), and (8). We create the bond portfolios by forming value-weighted portfolios of all outstanding bonds by firm. Investment (speculative) grade bonds have a rating equal to or above (below) BBB– at the end of month $t-1$. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month $t-1$ and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls also used in the main paper. Bond illiquidity is a bond's daily-price-change autocovariance (see Bao et al. (2011)), while its liquidity beta is its loading on the orthogonalized aggregate signed volume coefficient obtained from first-stage regressions (see Lin et al. (2011)). Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard (Bartram et al. (2025; BGN)) returns.

| | All Bonds | All Bonds | All Bonds | All Bonds | IG Bonds | IG Bonds | SG Bonds | SG Bonds |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *HighDistress* | –0.40 | –0.42 | –0.32 | –0.33 | –0.21 | –0.21 | –0.59 | –0.59 |
| | [–4.24] | [–4.41] | [–3.82] | [–4.01] | [–2.69] | [–2.69] | [–4.93] | [–5.30] |
| *LowDistress* | 0.07 | 0.08 | 0.06 | 0.07 | 0.07 | 0.07 | 0.15 | 0.15 |
| | [2.85] | [3.09] | [3.19] | [3.39] | [2.92] | [3.10] | [3.30] | [3.52] |
| *MarketBeta* | 0.03 | 0.02 | 0.05 | 0.05 | 0.03 | 0.02 | –0.02 | –0.02 |
| | [0.53] | [0.40] | [1.51] | [1.42] | [0.50] | [0.36] | [–0.36] | [–0.29] |
| *MarketSize* | –0.04 | –0.04 | –0.03 | –0.03 | –0.01 | –0.01 | –0.02 | –0.04 |
| | [–1.76] | [–1.92] | [–1.57] | [–1.98] | [–0.57] | [–0.48] | [–0.84] | [–1.29] |
| *BookToMarket* | –0.02 | –0.02 | 0.00 | –0.01 | 0.00 | 0.00 | –0.01 | –0.02 |
| | [–1.00] | [–1.31] | [–0.28] | [–0.51] | [0.22] | [0.35] | [–0.19] | [–0.71] |
| *Momentum* | 0.08 | 0.10 | 0.09 | 0.11 | 0.18 | 0.19 | –0.04 | –0.03 |
| | [0.85] | [1.20] | [1.11] | [1.52] | [2.74] | [3.21] | [–0.33] | [–0.27] |
| *AssetGrowth* | 0.01 | 0.01 | 0.06 | 0.05 | 0.00 | 0.01 | –0.02 | –0.03 |
| | [0.33] | [0.26] | [1.47] | [1.28] | [–0.03] | [0.25] | [–0.37] | [–0.41] |
| *Profitability* | –0.02 | –0.05 | –0.05 | –0.07 | –0.07 | –0.08 | 0.08 | 0.06 |
| | [–0.28] | [–0.90] | [–0.80] | [–1.32] | [–1.47] | [–1.54] | [0.55] | [0.39] |
| *BondMarketBeta* | 0.27 | 0.22 | 0.09 | 0.03 | 0.45 | 0.42 | 0.20 | 0.19 |
| | [1.24] | [1.12] | [0.43] | [0.13] | [1.29] | [1.18] | [0.76] | [0.82] |
| *BondSize* | –0.07 | –0.06 | –0.17 | –0.16 | –0.07 | –0.07 | –0.11 | –0.10 |
| | [–3.17] | [–2.92] | [–5.54] | [–5.49] | [–3.41] | [–3.55] | [–2.90] | [–2.90] |
| *BondMaturity* | 0.14 | 0.14 | 0.13 | 0.13 | 0.13 | 0.12 | 0.21 | 0.20 |
| | [2.35] | [2.29] | [2.91] | [3.00] | [2.23] | [2.16] | [2.45] | [2.42] |
| *BondCreditRating* | 0.17 | 0.14 | 0.10 | 0.08 | 0.10 | 0.09 | 0.60 | 0.52 |
| | [2.77] | [2.53] | [1.48] | [1.34] | [2.08] | [1.92] | [2.28] | [1.99] |
| *BondDownsideRisk* | 3.70 | 3.12 | 3.84 | 3.50 | 3.40 | 3.32 | 3.62 | 3.32 |
| | [2.85] | [2.56] | [3.14] | [3.20] | [2.83] | [2.79] | [2.54] | [2.41] |

(continued on next page)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *BondReversal* | –21.60 | –22.06 | –16.91 | –17.29 | –24.32 | –24.73 | –18.65 | –19.00 |
| | [–11.39] | [–12.39] | [–10.75] | [–12.03] | [–11.84] | [–12.75] | [–9.83] | [–10.14] |
| *BondIlliquidity* | | 0.03 | | 0.00 | | 0.04 | | 0.01 |
| | | [1.11] | | [–0.10] | | [1.56] | | [0.47] |
| *BondLiquidityBeta* | | 0.13 | | 0.04 | | 0.14 | | 0.07 |
| | | [1.13] | | [0.48] | | [1.46] | | [0.63] |
| Return Type | ME-ME | ME-ME | BGN | BGN | ME-ME | ME-ME | ME-ME | ME-ME |

## Table IA.11: Stock, Bond, Loan, & Asset Distress Portfolios: Transaction-Price Subsample

The table offers the monthly alphas of stock (Panel A), bond (Panel B), loan (Panel C), and firm-asset (Panel D) portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample exclusively using TRACE transaction prices to calculate bond returns. The first and second subpanels in Panels B to D focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific stocks, bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), firm-asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month $t$, where we use a firm's total stock, bond, loan, and firm-asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] ("Middle–Low" ("High–Middle") ["High–Low"]). FF6S and FF7S indicate the Fama and French (2016) six-factor model and the same model plus a stock liquidity factor; SB14 and SB15 indicate the 14-factor stock-bond model and the same model plus a bond liquidity factor; and SB17 and SB18 indicate the 17-factor stock-bond model and the same model plus a stock and bond liquidity factor, all respectively. The stock liquidity factor is constructed from Pástor and Stambaugh's (2003) liquidity proxy, whereas the bond liquidity factor is constructed from Bao et al.'s (2011) illiquidity proxy. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

| | Value-Weighted Portfolios | | Equally-Weighted Portfolios | |
|---|---|---|---|---|
| | Monthly Alpha | Monthly Alpha (incl. Liquidity Control) | Monthly Alpha | Monthly Alpha (incl. Liquidity Control) |
| | (1) | (2) | (3) | (4) |
| Panel A: Stock Returns (Mean Monthly # Per Porfolio: 33) | | | | |
| Middle–Low | 0.20 | 0.25 | 0.30 | 0.32 |
| | [0.97] | [1.19] | [1.74] | [1.91] |
| High–Middle | –0.58 | –0.59 | –0.68 | –0.82 |
| | [–1.53] | [–1.58] | [–1.90] | [–2.39] |
| High–Low | –0.38 | –0.34 | –0.38 | –0.50 |
| | [–1.00] | [–0.86] | [–1.05] | [–1.43] |
| Alpha Factors | FF6S | FF7S | FF6S | FF7S |
| Panel B: Firm-Level Bond Returns | | | | |
| Panel B.1: Month-End to Month-End Bond Returns (Mean Monthly # Per Porfolio: 17) | | | | |
| Middle–Low | –0.13 | –0.14 | –0.23 | –0.22 |
| | [–1.14] | [–1.15] | [–2.19] | [–2.22] |
| High–Middle | –0.73 | –0.72 | –0.54 | –0.55 |
| | [–3.78] | [–3.67] | [–2.88] | [–2.93] |
| High–Low | –0.86 | –0.85 | –0.76 | –0.77 |
| | [–5.11] | [–5.11] | [–4.80] | [–4.73] |
| Panel B.2: Bartram, Grinblatt and Nozawa (2025) Bond Returns (Mean Monthly # Per Porfolio: 21) | | | | |
| Middle–Low | –0.09 | –0.10 | –0.14 | –0.15 |
| | [–1.14] | [–1.17] | [–1.84] | [–1.92] |

(continued on next page)

| | | | | |
|---|---|---|---|---|
| Panel B.2: Bartram, Grinblatt and Nozawa (2025) Bond Returns (continued) | | | | |
| High–Middle | –0.63 | –0.62 | –0.47 | –0.46 |
| | [–4.21] | [–4.23] | [–3.16] | [–3.10] |
| High–Low | –0.72 | –0.72 | –0.61 | –0.61 |
| | [–4.88] | [–4.87] | [–4.23] | [–4.15] |
| Alpha Factors | SB14 | SB15 | SB14 | SB15 |
| Panel C: Firm-Level Loan Return | | | | |
| Panel C.1: Month-End to Month-End Loan Returns (Mean Monthly # Per Porfolio: 33) | | | | |
| Middle–Low | –0.04 | –0.04 | –0.03 | –0.04 |
| | [–1.28] | [–1.54] | [–1.00] | [–1.35] |
| High–Middle | –0.22 | –0.24 | –0.21 | –0.22 |
| | [–1.95] | [–2.03] | [–1.93] | [–1.93] |
| High–Low | –0.26 | –0.28 | –0.25 | –0.26 |
| | [–2.10] | [–2.23] | [–2.11] | [–2.17] |
| Panel C.2: Bartram, Grinblatt and Nozawa (2025) Loan Returns (Mean Monthly # Per Porfolio: 38) | | | | |
| Middle–Low | –0.07 | –0.08 | –0.03 | –0.04 |
| | [–1.68] | [–1.89] | [–0.91] | [–1.38] |
| High–Middle | –0.16 | –0.17 | –0.18 | –0.19 |
| | [–2.28] | [–2.33] | [–2.15] | [–2.17] |
| High–Low | –0.23 | –0.25 | –0.22 | –0.23 |
| | [–2.50] | [–2.63] | [–2.24] | [–2.35] |
| Alpha Factors | SB14 | SB15 | SB14 | SB15 |
| Panel D: Firm-Asset Returns | | | | |
| Panel D.1: Month-End to Month-End Firm-Asset Returns (Mean Monthly # Per Porfolio: 33) | | | | |
| Middle–Low | 0.07 | 0.09 | 0.20 | 0.20 |
| | [0.41] | [0.52] | [1.91] | [1.91] |
| High–Middle | –0.74 | –0.74 | –0.80 | –0.80 |
| | [–3.55] | [–3.46] | [–4.88] | [–4.87] |
| High–Low | –0.67 | –0.65 | –0.60 | –0.60 |
| | [–2.36] | [–2.31] | [–3.31] | [–3.31] |
| Panel D.2: Bartram, Grinblatt and Nozawa (2025) Firm-Asset Returns (Mean Monthly # Per Porfolio: 38) | | | | |
| Middle–Low | 0.02 | 0.02 | 0.16 | 0.14 |
| | [0.18] | [0.17] | [1.70] | [1.51] |
| High–Middle | –0.50 | –0.50 | –0.62 | –0.63 |
| | [–2.81] | [–2.76] | [–4.49] | [–4.44] |
| High–Low | –0.47 | –0.48 | –0.46 | –0.48 |
| | [–2.06] | [–2.02] | [–2.90] | [–2.89] |
| Alpha Factors | SB17 | SB18 | SB17 | SB18 |

## Table IA.12: Stock, Bond, Loan, and Asset Regressions on Distress Risk: Transaction-Price Subsample

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of stocks, firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios over month $t$ on two distress dummy variables and controls at the end of month $t-1$ in the stock-bond-loan-asset sample exclusively using TRACE transaction prices to calculate bond returns and controlling for illiquidity and liquidity risk in columns (3) and (5). We create the bond (loan) [firm asset] portfolios by forming value-weighted portfolios of all outstanding bonds (loans) [firm assets] by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month $t-1$ and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls also used in the main paper. Bond illiquidity is a bond's daily-price-change autocovariance (see Bao et al. (2011)), while its liquidity beta is its loading on the orthogonalized aggregate signed volume coefficient obtained from first-stage regressions (see Lin et al. (2011)). Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard (Bartram et al. (2025; BGN)) returns.

| | Stocks with Loans | Bonds with Stocks & Loans | | Bonds with Stocks & Loans | | Loans with Stocks | | Firm Assets with Stocks & Loans | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *HighDistress* | –1.07 | –0.82 | –0.97 | –0.43 | –0.47 | –0.33 | –0.16 | –0.87 | –0.45 |
| | [–2.33] | [–2.66] | [–2.56] | [–1.85] | [–1.92] | [–1.78] | [–1.58] | [–4.18] | [–1.97] |
| *LowDistress* | 0.14 | 0.19 | 0.24 | 0.25 | 0.26 | 0.02 | 0.04 | 0.14 | 0.16 |
| | [0.39] | [2.04] | [2.29] | [1.90] | [2.03] | [0.34] | [0.65] | [0.92] | [1.40] |
| *MarketBeta* | 0.33 | 0.00 | –0.03 | 0.06 | 0.05 | 0.04 | 0.04 | 0.09 | 0.10 |
| | [1.24] | [0.01] | [–0.28] | [0.57] | [0.62] | [0.52] | [0.66] | [0.65] | [0.77] |
| *MarketSize* | –0.13 | –0.14 | –0.13 | –0.15 | –0.11 | 0.01 | 0.00 | –0.04 | –0.03 |
| | [–1.60] | [–2.20] | [–2.11] | [–2.07] | [–1.77] | [0.67] | [0.32] | [–0.95] | [–0.78] |
| *BookToMarket* | –0.20 | –0.08 | –0.06 | –0.07 | –0.07 | 0.01 | –0.01 | –0.11 | –0.13 |
| | [–1.55] | [–1.39] | [–1.21] | [–1.46] | [–1.72] | [0.18] | [–0.30] | [–1.74] | [–2.32] |
| *Momentum* | –0.05 | 0.07 | –0.01 | 0.12 | 0.10 | 0.19 | 0.14 | 0.06 | 0.14 |
| | [–0.10] | [0.30] | [–0.06] | [0.53] | [0.51] | [1.85] | [1.70] | [0.26] | [0.66] |
| *AssetGrowth* | –0.45 | –0.02 | 0.00 | –0.10 | 0.01 | –0.08 | –0.04 | –0.07 | 0.06 |
| | [–1.00] | [–0.14] | [0.01] | [–0.62] | [0.05] | [–0.94] | [–0.72] | [–0.42] | [0.38] |
| *Profitability* | –0.52 | –0.41 | –0.36 | –0.37 | –0.33 | 0.24 | 0.19 | –0.49 | –0.42 |
| | [–0.85] | [–1.05] | [–1.05] | [–1.07] | [–0.89] | [1.96] | [1.53] | [–1.20] | [–1.00] |
| *BondMarketBeta* | | 1.61 | 1.34 | 1.00 | 0.95 | | | | |
| | | [1.52] | [2.10] | [1.02] | [1.53] | | | | |
| *BondSize* | | 0.02 | 0.01 | 0.01 | 0.00 | | | | |
| | | [0.41] | [0.20] | [0.17] | [–0.04] | | | | |
| *BondMaturity* | | 0.19 | 0.34 | 0.20 | 0.24 | | | | |
| | | [1.21] | [1.97] | [1.58] | [1.93] | | | | |
| *BondCreditRating* | | 0.04 | 0.07 | 0.15 | 0.20 | | | | |
| | | [0.28] | [0.69] | [1.09] | [1.65] | | | | |

(continued on next page)

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *BondDownsideRisk* | | –2.56 | –1.85 | –1.88 | 0.11 | | | | |
| | | [–0.91] | [–0.94] | [–0.60] | [0.05] | | | | |
| *BondReversal* | | –12.87 | –15.03 | –13.72 | –14.84 | | | | |
| | | [–4.41] | [–4.97] | [–4.52] | [–4.83] | | | | |
| *BondIlliquidity* | | | –0.04 | | –0.09 | | | | |
| | | | [–0.68] | | [–1.98] | | | | |
| *BondLiquidityBeta* | | | 0.18 | | 0.04 | | | | |
| | | | [0.62] | | [0.16] | | | | |
| *LoanSize* | | –0.02 | –0.01 | 0.03 | 0.04 | –0.04 | –0.01 | –0.10 | –0.08 |
| | | [–0.55] | [–0.24] | [0.59] | [0.89] | [–2.19] | [–0.55] | [–1.60] | [–1.27] |
| *LoanMaturity* | | 0.06 | 0.07 | –0.04 | –0.04 | –0.03 | 0.01 | –0.06 | –0.13 |
| | | [0.50] | [0.57] | [–0.31] | [–0.43] | [–0.38] | [0.14] | [–0.61] | [–1.52] |
| Return Type | ME-ME | ME-ME | ME-ME | BGN | BGN | ME-ME | BGN | ME-ME | BGN |

### Table IA.13: Bond Distress Portfolios: M&A Adjustment

The table offers the SB14 alphas of bond portfolios univariately sorted on distress risk in the stock-bond sample reassigning surviving bonds to acquiring firms after a merger-and-acquisition (M&A) deal. While columns (1) and (3) focus on standard returns, columns (2) and (4) concentrate on Bartram et al. (2025; BGN) returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm) into portfolios according to the decile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We value (columns (1) and (2)) or equally ((3) and (4)) weight the portfolios and hold them over month $t$, where we use a firm's total bond capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the fifth (top) [top] decile portfolio and short the bottom (fifth) [bottom] ("Middle–Low" ("High–Middle") ["High–Low"]). SB14 indicates the 14-factor stock-bond model. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

| | Value-Weighted Portfolios | | Equally-Weighted Portfolios | |
|---|---|---|---|---|
| | St. Return Monthly Alpha | BGN Return Monthly Alpha | St. Return Monthly Alpha | BGN Return Monthly Alpha |
| | (1) | (2) | (3) | (4) |
| Medium–Low | –0.06 | –0.07 | –0.07 | –0.07 |
| | [–2.05] | [–2.26] | [–2.99] | [–3.18] |
| High–Middle | –0.41 | –0.41 | –0.35 | –0.34 |
| | [–6.24] | [–6.20] | [–6.36] | [–6.31] |
| High–Low | –0.47 | –0.47 | –0.42 | –0.41 |
| | [–7.66] | [–7.72] | [–7.29] | [–7.22] |
| Alpha Factors | SB14 | SB14 | SB14 | SB14 |

## Table IA.14: Bond Regressions on Distress Risk: M&A Adjustment

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of all, investment-grade (IG), and speculative-grade (SG) firm-specific bond portfolios over month $t$ on two distress dummy variables and controls at the end of month $t-1$ in the stock-bond sample reassigning surviving bonds to acquiring firms after a merger-and-acquisition (M&A) deal. We create the bond portfolios by forming value-weighted portfolios of all outstanding bonds by firm. Investment (speculative) grade bonds have a rating equal to or above (below) BBB– at the end of month $t-1$. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month $t-1$ and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard (Bartram et al. (2025; BGN)) returns.

| | All Bonds | All Bonds | IG Bonds | IG Bonds | SG Bonds | SG Bonds |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *HighDistress* | –0.26 | –0.25 | –0.12 | –0.11 | –0.42 | –0.41 |
| | [–4.67] | [–4.64] | [–3.81] | [–3.47] | [–4.90] | [–4.93] |
| *LowDistress* | 0.06 | 0.05 | 0.04 | 0.04 | 0.10 | 0.09 |
| | [4.23] | [3.87] | [3.84] | [3.86] | [2.23] | [2.07] |
| *MarketBeta* | 0.05 | 0.05 | 0.01 | 0.01 | 0.05 | 0.06 |
| | [2.24] | [2.22] | [0.77] | [0.65] | [1.07] | [1.21] |
| *MarketSize* | –0.03 | –0.03 | –0.01 | –0.01 | –0.05 | –0.05 |
| | [–3.54] | [–3.53] | [–1.61] | [–1.54] | [–2.21] | [–2.24] |
| *BookToMarket* | 0.00 | 0.00 | –0.01 | –0.01 | 0.00 | 0.00 |
| | [–0.25] | [–0.22] | [–1.21] | [–1.11] | [–0.07] | [–0.05] |
| *Momentum* | 0.08 | 0.08 | 0.13 | 0.13 | –0.11 | –0.12 |
| | [1.75] | [1.75] | [3.50] | [3.57] | [–1.01] | [–1.07] |
| *AssetGrowth* | 0.05 | 0.05 | 0.02 | 0.03 | –0.06 | –0.06 |
| | [1.30] | [1.46] | [0.79] | [1.03] | [–0.76] | [–0.82] |
| *Profitability* | 0.01 | 0.00 | –0.03 | –0.04 | –0.03 | –0.05 |
| | [0.32] | [0.07] | [–1.13] | [–1.39] | [–0.23] | [–0.36] |
| *BondMarketBeta* | 0.11 | 0.09 | –0.09 | –0.12 | 0.24 | 0.25 |
| | [1.12] | [0.99] | [–0.78] | [–0.87] | [1.50] | [1.58] |
| *BondSize* | –0.03 | –0.04 | –0.03 | –0.05 | –0.02 | –0.03 |
| | [–1.44] | [–2.18] | [–1.93] | [–2.80] | [–0.51] | [–0.61] |
| *BondMaturity* | 0.08 | 0.07 | 0.08 | 0.07 | 0.06 | 0.07 |
| | [2.37] | [2.38] | [2.49] | [2.46] | [1.06] | [1.22] |
| *BondCreditRating* | 0.11 | 0.10 | 0.07 | 0.05 | 0.24 | 0.23 |
| | [2.69] | [2.53] | [2.39] | [1.83] | [1.24] | [1.18] |
| *BondDownsideRisk* | 3.77 | 3.79 | 2.51 | 2.67 | 2.17 | 2.02 |
| | [4.41] | [4.44] | [3.08] | [3.22] | [1.50] | [1.41] |
| *BondReversal* | –9.77 | –9.79 | –9.08 | –8.98 | –7.61 | –7.73 |
| | [–5.45] | [–5.54] | [–5.61] | [–5.60] | [–3.86] | [–3.95] |
| Return Type | ME-ME | BGN | ME-ME | BGN | ME-ME | BGN |

### Table IA.15: Bond, Loan, & Asset Distress Portfolios: M&A Adjustment

The table offers the monthly alphas of bond, loan, and firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample reassigning surviving bonds and loans to acquiring firms after a merger-and-acquisition (M&A) deal. Panels A and B focus on standard and Bartram et al. (2025; BGN) bond returns, respectively. We sort our sample firm-specific bond portfolios (i.e., the value-weighted portfolios of all outstanding bonds by firm), firm-specific loan portfolios (i.e., the value-weighted portfolios of all outstanding loans by firm), and firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We value (columns (1) to (3)) or equally ((4) to (6)) weight the portfolios and hold them over month $t$, where we use a firm's total bond, loan, and firm-asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] ("Middle–Low" ("High–Middle") ["High–Low"]). SB14 and SB17 indicate the 14 and 17-factor stock-bond model, respectively. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

| | Value-Weighted Portfolios | | | Equally-Weighted Portfolios | | |
|---|---|---|---|---|---|---|
| | Bond Monthly Alpha | Loan Monthly Alpha | Firm-Asset Monthly Alpha | Bond Monthly Alpha | Loan Monthly Alpha | Firm-Asset Monthly Alpha |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Month-End to Month-End Returns | | | | | | |
| Medium–Low | 0.00 | –0.03 | 0.21 | –0.09 | –0.03 | 0.36 |
| | [–0.04] | [–0.88] | [0.92] | [–1.24] | [–1.08] | [1.98] |
| High–Middle | –0.85 | –0.34 | –0.88 | –0.65 | –0.33 | –0.85 |
| | [–3.83] | [–3.06] | [–3.49] | [–3.12] | [–3.12] | [–4.56] |
| High–Low | –0.85 | –0.37 | –0.67 | –0.74 | –0.36 | –0.50 |
| | [–3.80] | [–3.05] | [–2.49] | [–3.70] | [–3.27] | [–2.73] |
| Panel B: Bartram, Grinblatt and Nozawa (2025) Returns | | | | | | |
| Medium–Low | –0.05 | –0.06 | 0.31 | –0.10 | 0.00 | 0.40 |
| | [–0.78] | [–1.50] | [1.28] | [–1.47] | [–0.07] | [2.32] |
| High–Middle | –0.88 | –0.27 | –0.87 | –0.70 | –0.30 | –0.82 |
| | [–4.20] | [–2.88] | [–3.39] | [–3.65] | [–3.35] | [–4.68] |
| High–Low | –0.93 | –0.32 | –0.56 | –0.80 | –0.30 | –0.42 |
| | [–4.27] | [–3.21] | [–2.47] | [–4.15] | [–3.21] | [–2.77] |
| Alpha Factors | SB14 | SB14 | SB17 | SB14 | SB14 | SB17 |

### Table IA.16: Bond, Loan, & Asset Regressions on Distress Risk: M&A Adjustment

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of firm-specific bond portfolios, firm-specific loan portfolios, and firm-specific asset portfolios over month $t$ on two distress dummy variables and controls at the end of month $t-1$ in the stock-bond-loan-asset sample reassigning surviving bonds and loans to acquiring firms after a merger-and-acquisition (M&A) deal. We create the bond (loan) [firm asset] portfolios by forming value-weighted portfolios of all outstanding bonds (loans) [firm assets] by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month $t-1$ and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard (Bartram et al. (2025; BGN)) returns.

| | Bonds with Stocks & Loans | | Loans with Stocks | | Firm Assets with Stocks & Loans | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *HighDistress* | −0.84 | −0.98 | −0.54 | −0.42 | −0.76 | −0.86 |
| | [−2.87] | [−3.38] | [−2.82] | [−3.22] | [−2.98] | [−3.08] |
| *LowDistress* | 0.21 | 0.09 | 0.01 | −0.01 | 0.03 | −0.06 |
| | [2.39] | [0.72] | [0.25] | [−0.18] | [0.29] | [−0.45] |
| *MarketBeta* | −0.03 | −0.01 | −0.01 | 0.00 | 0.01 | −0.08 |
| | [−0.36] | [−0.15] | [−0.13] | [−0.01] | [0.05] | [−0.58] |
| *MarketSize* | −0.11 | −0.15 | 0.00 | −0.01 | −0.08 | −0.08 |
| | [−2.71] | [−3.03] | [−0.09] | [−0.56] | [−1.74] | [−1.82] |
| *BookToMarket* | 0.01 | 0.05 | 0.00 | −0.03 | −0.03 | −0.07 |
| | [0.26] | [0.77] | [−0.13] | [−1.26] | [−0.37] | [−1.08] |
| *Momentum* | 0.06 | 0.19 | 0.19 | 0.18 | 0.21 | 0.39 |
| | [0.28] | [0.95] | [2.11] | [2.22] | [0.88] | [1.59] |
| *AssetGrowth* | 0.07 | −0.03 | −0.04 | −0.02 | −0.09 | −0.12 |
| | [0.48] | [−0.21] | [−0.59] | [−0.45] | [−0.67] | [−0.98] |
| *Profitability* | −0.19 | 0.02 | 0.21 | 0.23 | 0.02 | 0.02 |
| | [−0.72] | [0.10] | [1.66] | [1.89] | [0.05] | [0.06] |
| *BondMarketBeta* | 0.89 | 1.18 | | | | |
| | [1.05] | [1.34] | | | | |
| *BondSize* | 0.02 | 0.01 | | | | |
| | [0.61] | [0.16] | | | | |
| *BondMaturity* | 0.19 | 0.25 | | | | |
| | [2.01] | [1.92] | | | | |
| *BondCreditRating* | 0.34 | 0.34 | | | | |
| | [2.42] | [2.58] | | | | |
| *BondDownsideRisk* | −0.88 | −2.87 | | | | |
| | [−0.33] | [−0.85] | | | | |
| *BondReversal* | −8.70 | −9.58 | | | | |
| | [−2.73] | [−3.06] | | | | |

(continued on next page)

| | | | | | | |
|---|---|---|---|---|---|---|
| *LoanSize* | –0.04 | –0.05 | –0.02 | 0.00 | –0.09 | –0.07 |
| | [–0.89] | [–1.04] | [–0.94] | [0.11] | [–1.72] | [–1.35] |
| *LoanMaturity* | 0.05 | –0.19 | –0.08 | –0.02 | –0.03 | –0.10 |
| | [0.60] | [–0.90] | [–1.24] | [–0.39] | [–0.32] | [–1.08] |
| Return Type | ME-ME | BGN | ME-ME | BGN | ME-ME | BGN |

## Table IA.17: The Equity and Liability Structure of Our Sample Firms

The table offers descriptive statistics on the proportions of current liabilities (first subpanel), long-term liabilities (second subpanel), and equities (third subpanel) of the firms in Compustat (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999 to 2020 sample period. The descriptive statistics include the number of observations, the mean, the standard deviation (St. Dev.), and the fifth, 25th, 50th, 75th, and 95th percentile, first calculated by fiscal year and then averaged over time. The current liabilities are accounts payable, debt in current liabilities, income taxes payable, and other. We also report the share of other attributable to accrued expenses, if available. The long-term liabilities are long-term debt, deferred taxes and investment tax credits, non-controlling interests, and other. We also report the share of long-term debt attributable to capitalized leases. The equities are common and preferred equity.

| | | | St. | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Dev. | 5 | 25 | 50 | 75 | 95 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Full Sample (1999-2020) | | | | | | | | |
| Panel A.1: Current Liabilities | | | | | | | | |
| Accounts Payable | 4,775 | 0.08 | 0.09 | 0.00 | 0.02 | 0.05 | 0.10 | 0.26 |
| Debt in Current Liabilities | 4,775 | 0.06 | 0.12 | 0.00 | 0.00 | 0.01 | 0.05 | 0.31 |
| Income Taxes Payable | 4,775 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| Other | 4,775 | 0.12 | 0.12 | 0.00 | 0.04 | 0.09 | 0.16 | 0.37 |
| - Accrued Expenses | 3,905 | 0.07 | 0.07 | 0.00 | 0.03 | 0.05 | 0.09 | 0.19 |
| Panel A.2: Long-Term Liabilities | | | | | | | | |
| Long-Term Debt | 4,775 | 0.15 | 0.21 | 0.00 | 0.00 | 0.04 | 0.25 | 0.61 |
| - Capitalized Leases | 4,775 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| Def. Taxes and Inv. Tax Credits | 4,775 | 0.01 | 0.03 | 0.00 | 0.00 | 0.00 | 0.01 | 0.08 |
| Noncontrolling Interests | 4,775 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Other | 4,775 | 0.05 | 0.09 | 0.00 | 0.00 | 0.01 | 0.05 | 0.19 |
| Panel A.3: Equity | | | | | | | | |
| Common Equity | 4,775 | 0.49 | 0.28 | 0.01 | 0.27 | 0.51 | 0.73 | 0.92 |
| Preferred Equity | 4,775 | 0.03 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.19 |
| Panel B: Firm-Asset Sample (1999–2020) | | | | | | | | |
| Panel B.1: Current Liabilities | | | | | | | | |
| Accounts Payable | 151 | 0.06 | 0.06 | 0.01 | 0.02 | 0.04 | 0.09 | 0.18 |
| Debt in Current Liabilities | 151 | 0.02 | 0.06 | 0.00 | 0.00 | 0.01 | 0.02 | 0.08 |
| Income Taxes Payable | 151 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 |
| Other | 151 | 0.09 | 0.07 | 0.02 | 0.05 | 0.07 | 0.11 | 0.21 |
| - Accrued Expenses | 136 | 0.06 | 0.04 | 0.01 | 0.03 | 0.05 | 0.07 | 0.13 |

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| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel B.2: Long-Term Liabilities | | | | | | | | |
| Long-Term Debt | 151 | 0.43 | 0.22 | 0.04 | 0.28 | 0.42 | 0.59 | 0.79 |
| - Capitalized Leases | 151 | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 |
| Def. Taxes and Inv. Tax Credits | 151 | 0.03 | 0.04 | 0.00 | 0.00 | 0.02 | 0.06 | 0.12 |
| Noncontrolling Interests | 151 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| Other | 151 | 0.06 | 0.07 | 0.00 | 0.01 | 0.03 | 0.08 | 0.18 |
| Panel B.3: Equity | | | | | | | | |
| Common Equity | 151 | 0.28 | 0.20 | 0.00 | 0.12 | 0.28 | 0.42 | 0.64 |
| Preferred Equity | 151 | 0.01 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 |

## Table IA.18: The Debt Structure of Our Sample Firms

The table offers descriptive statistics on the proportions of debt instruments of the firms in Compustat (Panel A) and the stock-bond-loan-asset subsample (Panel B) over the 1999 to 2020 sample period. The descriptive statistics include the number of observations, the mean, the standard deviation (St. Dev.), and the fifth, 25th, 50th, 75th, and 95th percentile, first calculated by fiscal year and then averaged over time. The debt instruments are commercial paper, revolving credit lines, term loans, senior bonds, subordinated bonds, capital leases, trust preferred funds, general other borrowing, and the residual adjustment. The residual adjustment is calculated by Capital IQ to ensure that the proportions sum up to 100%.

| | | | St. | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Dev. | 5 | 25 | 50 | 75 | 95 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Full Sample (1999-2020) | | | | | | | | |
| Commercial Paper | 5,923 | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| Revolving Credit Lines | 5,923 | 0.16 | 0.29 | 0.00 | 0.00 | 0.01 | 0.15 | 0.97 |
| Term Loans | 5,923 | 0.27 | 0.36 | 0.00 | 0.00 | 0.02 | 0.53 | 0.98 |
| Senior Bonds | 5,923 | 0.36 | 0.41 | 0.00 | 0.00 | 0.11 | 0.77 | 1.00 |
| Subordinated Bonds | 5,923 | 0.05 | 0.16 | 0.00 | 0.00 | 0.00 | 0.02 | 0.33 |
| Capital Leases | 5,923 | 0.06 | 0.19 | 0.00 | 0.00 | 0.00 | 0.02 | 0.35 |
| Trust Preferred Funds | 5,923 | 0.01 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 |
| General Other Borrowing | 5,923 | 0.09 | 0.24 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 |
| Residual Adjustment | 5,923 | –0.01 | 0.08 | –0.06 | 0.00 | 0.00 | 0.00 | 0.03 |
| Panel B: Firm-Asset Sample (1999–2020) | | | | | | | | |
| Commercial Paper | 211 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| Revolving Credit Lines | 211 | 0.09 | 0.18 | 0.00 | 0.00 | 0.02 | 0.09 | 0.50 |
| Term Loans | 211 | 0.43 | 0.35 | 0.00 | 0.10 | 0.39 | 0.74 | 0.98 |
| Senior Bonds | 211 | 0.32 | 0.33 | 0.00 | 0.00 | 0.20 | 0.58 | 0.94 |
| Subordinated Bonds | 211 | 0.09 | 0.16 | 0.00 | 0.00 | 0.01 | 0.14 | 0.41 |
| Capital Leases | 211 | 0.03 | 0.08 | 0.00 | 0.00 | 0.00 | 0.02 | 0.11 |
| Trust Preferred Funds | 211 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| General Other Borrowing | 211 | 0.04 | 0.14 | 0.00 | 0.00 | 0.00 | 0.01 | 0.29 |
| Residual Adjustment | 211 | 0.00 | 0.05 | –0.03 | –0.01 | 0.00 | 0.00 | 0.02 |

## Table IA.19: Asset Distress Portfolios: Alternative Firm-Asset Returns

The table offers the SB17 alphas of firm-asset portfolios univariately sorted on distress risk in the stock-bond-loan-asset sample based on alternative firm-asset returns. Panels A and B focus on standard and Bartram et al. (2025; BGN) returns, respectively. Columns (1) and (5) rely on our original asset returns also used in our main tests, columns (2) and (6) on asset returns including trade credit as fourth asset class, columns (3) and (7) on asset returns exploiting Capital IQ data to adjust the asset-class weights, and columns (4) and (8) on asset returns exploiting Compustat and Mergent FISD data to adjust the asset-class weights. We sort our sample firm-specific asset portfolios (the value-weighted portfolios of the stock, bond portfolio, and loan portfolio by firm) into portfolios according to the quintile breakpoints of Campbell et al. (2008) distress risk at the end of month $t-1$. We value (columns (1) to (4)) or equally ((5) to (8)) weight the portfolios and hold them over month $t$, where we use a firm's total asset capitalization to construct the value-weights. We form three spread portfolios, the first (second) [third] long the middle (top) [top] quintile portfolio and short the bottom (middle) [bottom] ("Middle–Low" ("High–Middle") ["High–Low"]). SB17 indicates the 17-factor stock-bond model. Plain numbers are monthly estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics with a twelve-month lag length. To be concise, the table reports only the spread portfolio alphas.

| | Value-Weighted Portfolios | | | | Equally-Weighted Portfolios | | | |
|---|---|---|---|---|---|---|---|---|
| | Original Returns | Trade Credit Adjusted Returns | Loan Weight Adjusted Returns | Bond-Loan Weight Adjusted Returns | Original Returns | Trade Credit Adjusted Returns | Loan Weight Adjusted Returns | Bond-Loan Weight Adjusted Returns |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A: Month-End to Month-End Firm-Asset Returns** | | | | | | | | |
| Middle–Low | 0.14 | 0.23 | 0.11 | 0.21 | 0.31 | 0.32 | 0.29 | 0.33 |
| | [0.62] | [1.30] | [0.50] | [1.23] | [1.77] | [2.35] | [1.60] | [1.80] |
| High–Middle | –0.80 | –0.77 | –0.75 | –0.77 | –0.83 | –0.76 | –0.82 | –0.74 |
| | [–3.41] | [–3.79] | [–3.29] | [–3.00] | [–4.46] | [–4.82] | [–4.51] | [–3.43] |
| High–Low | –0.66 | –0.54 | –0.63 | –0.56 | –0.52 | –0.44 | –0.53 | –0.42 |
| | [–2.71] | [–2.63] | [–2.76] | [–2.71] | [–2.88] | [–2.76] | [–2.94] | [–2.58] |
| **Panel B: Bartram, Grinblatt and Nozawa (2025) Firm-Asset Returns** | | | | | | | | |
| Middle–Low | 0.23 | 0.29 | 0.19 | 0.21 | 0.38 | 0.37 | 0.37 | 0.36 |
| | [1.09] | [1.68] | [0.94] | [1.54] | [2.45] | [3.02] | [2.35] | [2.33] |
| High–Middle | –0.73 | –0.70 | –0.67 | –0.59 | –0.76 | –0.69 | –0.73 | –0.65 |
| | [–3.15] | [–3.42] | [–2.98] | [–2.85] | [–4.78] | [–5.14] | [–4.72] | [–3.68] |
| High–Low | –0.50 | –0.42 | –0.47 | –0.37 | –0.38 | –0.32 | –0.37 | –0.29 |
| | [–2.63] | [–2.64] | [–2.69] | [–2.38] | [–2.52] | [–2.42] | [–2.40] | [–2.19] |
| Alphas | SB17 | SB17 | SB17 | SB17 | SB17 | SB17 | SB17 | SB17 |

## Table IA.20: Firm-Asset Regressions on Distress Risk: Alternative Firm-Asset Returns

The table offers the results from Fama and MacBeth (1973) regressions of the excess returns of firm assets over month $t$ on two distress dummy variables and controls at the end of month $t-1$ in the stock-bond-loan-asset sample based on alternative firm-asset returns. Columns (1) and (2) rely on our original asset returns also used in our main tests, columns (3) and (4) on asset returns including trade credit as fourth asset class, columns (5) and (6) on asset returns exploiting Capital IQ data to adjust the asset-class weights, and columns (7) and (8) on asset returns exploiting Compustat and Mergent FISD data to adjust the asset-class weights. We create the firm asset portfolios by forming value-weighted portfolios of all firm assets by firm. The first (second) distress dummy, *HighDistress* (*LowDistress*), is equal to one if Campbell et al. (2008) distress risk is within the top decile (below the median) at the end of month $t-1$ and else zero. See Table A1 in Appendix A at the end of the main paper for details about the controls. Plain numbers are monthly premium estimates (in %), while those in square parentheses are Newey and West (1987) $t$-statistics calculated with a twelve-month lag length. The columns labelled "ME-ME" ("BGN") rely on standard (Bartram et al. (2025; BGN)) returns.

| | Original Asset Returns (for comparison) | | Trade Credit Adjusted Asset Returns | | Loan Weight Adjusted Asset Returns | | Bond + Loan Weight Adjusted Asset Returns | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *HighDistress* | –0.79 | –0.75 | –0.65 | –0.63 | –0.80 | –0.68 | –0.54 | –0.47 |
| | [–3.21] | [–3.09] | [–3.31] | [–3.13] | [–3.36] | [–3.47] | [–2.56] | [–2.33] |
| *LowDistress* | 0.02 | 0.00 | 0.01 | –0.01 | –0.03 | –0.04 | 0.09 | 0.04 |
| | [0.12] | [–0.00] | [0.11] | [–0.08] | [–0.22] | [–0.32] | [0.86] | [0.34] |
| *MarketBeta* | 0.01 | –0.08 | –0.04 | –0.11 | –0.01 | –0.12 | –0.05 | –0.16 |
| | [0.05] | [–0.52] | [–0.32] | [–0.80] | [–0.11] | [–0.72] | [–0.45] | [–1.19] |
| *MarketSize* | –0.06 | –0.07 | –0.07 | –0.08 | –0.04 | –0.05 | –0.04 | –0.05 |
| | [–1.54] | [–1.66] | [–1.83] | [–1.96] | [–0.90] | [–1.23] | [–1.05] | [–1.31] |
| *BookToMarket* | –0.03 | –0.13 | –0.04 | –0.13 | –0.02 | –0.12 | 0.05 | 0.01 |
| | [–0.37] | [–1.40] | [–0.68] | [–1.60] | [–0.29] | [–1.34] | [0.57] | [0.15] |
| *Momentum* | 0.23 | 0.39 | 0.23 | 0.39 | 0.22 | 0.40 | 0.12 | 0.16 |
| | [0.96] | [1.69] | [1.10] | [1.89] | [0.92] | [1.75] | [0.49] | [0.66] |
| *AssetGrowth* | –0.02 | –0.02 | 0.01 | –0.01 | –0.07 | –0.07 | 0.09 | 0.05 |
| | [–0.15] | [–0.16] | [0.09] | [–0.05] | [–0.44] | [–0.53] | [0.76] | [0.45] |
| *Profitability* | 0.07 | 0.32 | 0.00 | 0.23 | 0.15 | 0.39 | 0.13 | 0.28 |
| | [0.17] | [0.69] | [0.01] | [0.59] | [0.34] | [0.82] | [0.46] | [0.90] |
| *LoanSize* | –0.09 | –0.05 | –0.08 | –0.04 | –0.10 | –0.06 | –0.10 | –0.05 |
| | [–1.50] | [–0.85] | [–1.55] | [–0.74] | [–1.66] | [–1.16] | [–2.35] | [–0.99] |
| *LoanMaturity* | –0.06 | –0.15 | 0.00 | –0.09 | –0.05 | –0.11 | 0.03 | –0.02 |
| | [–0.60] | [–1.53] | [–0.01] | [–1.10] | [–0.51] | [–1.15] | [0.49] | [–0.28] |
| Return Type | ME-ME | BGN | ME-ME | BGN | ME-ME | BGN | ME-ME | BGN |